THREE ESSAYS ON DERIVATIVES MARKETS

A Doctoral Dissertation

by
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Ankara
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OLUWAKAYODE JOHN OMOLE THREE ESSAYS ON DERIVATIVES MARKET Bilkent University
2022

To my family

THREE ESSAYS ON DERIVATIVES MARKETS

The Graduate School of Economics and Social Sciences

of

İhsan Doğramacı Bilkent University

by

OLUWAKAYODE JOHN OMOLE

In Partial Fulfillment of the Requirements for the Degree of

DOCTOR OF PHILOSOPHY IN MANAGEMENT

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İHSAN DOĞRAMACI BİLKENT UNIVERSITY

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January 2022

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a dissertation for the degree of Doctor of Philosophy.

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Supervisor

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a dissertation for the degree of Doctor of Philosophy.

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ABSTRACT

THREE ESSAYS ON DERIVATIVES MARKETS

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Ph.D. in Department of Management

Supervisor: Assoc. Prof. Dr. Ahmet Şensoy

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This thesis comprises of three essays on derivatives markets. The first essay revisits the model-free methodology of the implied volatility index (VIX) and its global counterparts as empirically estimated. Then, we modify the model parameter selection procedure to be compatible with the microstructure characteristics of emerging derivative markets. Applying this approach on Turkish market data, we introduce the implied volatility index of Borsa Istanbul (VBI). We find that VBI is a significant predictor of the future realized volatility, is significantly correlated with Turkey's own financial indicators, but not with many global financial indicators. Additionally, we find that the presence of implied volatility spillover from US equity market to Borsa Istanbul, but not the other way around. The second essay uses proprietary transaction level data of Borsa Istanbul to compute the order imbalance of index options to investigate the linkages between option trades and spot index returns. Our findings show that weeks with higher call (put) order imbalance are associated with higher (lower) contemporaneous spot index returns. In addition, higher call order imbalance significantly predicts negative next-week index returns. The result of the chapter is consistent with the view that the hedging demand of counterparties in the option market that leads to the transfer of order imbalance from option market to stock market drives the predictability of index call options. In the third essay, we investigate the existence of common effects in order imbalance in the Borsa Istanbul's option market. Accordingly, we find the presence of commonality in order imbalance for call options and an even more dominant presence in put options. The results suggest that, from the order imbalance perspective, equity order imbalance contributes more than options to explaining stock return variations.

Keywords: Borsa Istanbul, Commonality, Delta-hedging, Market Microstructure, Options market, Order Imbalance, VBI.

ÖZET

TÜREV PIYASALAR ÜZERINE ÜÇ MAKALE

Omole, Oluwakayode John

Doktora, Işletme

Tez Danışmanı: Assoc. Prof. Dr. Ahmet Şensoy

Ocak 2022

Bu tez türev piyasalar hakkında üç makaleden oluşmaktadır. İlk bölüm, ampirik olarak tahmin edildiği şekliyle zımni dalgalanma oranı endeksinin (VIX) modelsiz metodolojisini ve küresel muadillerini ele almaktadır. Ardından, model parametre seçim prosedürünün gelişen türev piyasaların mikroyapı özellikleriyle uyumlu olarak değişimi gösterilmektedir. Bu yaklaşım Türkiye piyasası verilerine uygulanarak Borsa İstanbul'un zımni dalgalanma oranı endeksi (VBI) tanıtılmaktadır. VBI'nin gelecekte gerçekleşen dalgalanmanın önemli bir tahmincisi olduğunu, Türkiye'nin kendi finansal göstergeleri ile önemli ölçüde ilişkili olduğunu, ancak birçok küresel finansal gösterge ile ilişkili olmadığını gözlemlemekteyiz. Ek olarak, ABD hisse senedi piyasasından Borsa İstanbul'a zımni volatilite yayılımının varlığını, ancak bunun tersinin var olmadığını tespit etmekteyiz. İkinci makale, opsiyon işlemleri ile spot endeks getirileri arasındaki bağlantıları araştırmak amacıyla endeks opsiyonlarının emir dengesizliğini hesaplamak için Borsa İstanbul'un tescilli işlem seviyesi verilerini kullanmaktadır. Bulgularımız, daha yüksek alım (satım) emri dengesizliği olan haftaların, daha yüksek (düşük) eş zamanlı spot endeks getirileri ile ilişkili olduğunu göstermektedir. Ek olarak, daha yüksek alım emri dengesizliği, gelecek hafta negatif endeks getirilerini önemli ölçüde öngörmektedir. Bu bölümün sonucu, opsiyon piyasasındaki karşı tarafların riskten korunma talebinin, opsiyon piyasasından hisse senedi piyasasına emir dengesizliği transferine yol açmasının endeks alım opsiyonlarının öngörülebilirliğini yönlendirdiği görüşüyle tutarlıdır. Üçüncü makalede, Borsa İstanbul opsiyon piyasasında emir dengesizliğinde ortak etkilerin varlığı araştırılmaktadır. Buna göre, alım opsiyonlarında emir dengesizliğinde ortaklığın varlığı tespit edilirken, satım opsiyonlarındaki

varlığının çok daha baskın olduğu gözlemlenmektedir. Sonuçlar, emir dengesizliği perspektifinden bakıldığında, hisse senedi emir dengesizliğinin, hisse senedi getirisi değişimlerini açıklamaya opsiyonlardan daha fazla katkıda bulunduğunu göstermektedir.

Anahtar sözcükler: Borsa İstanbul, Ortaklığı, Delta Riskten Korunma, Piyasa Mikroyapısı, Opsiyon Piyasası, Emir Dengesizliği, Borsa İstanbul'un Oynaklığı.

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CHAPTER 1

INTRODUCTION

1.1. Overview

This dissertation focuses on the market microstructure of the equity options market. Market microstructure literature is a subset of financial economics that is primarily concerned with trade processes and outcomes. As the financial market continues to evolve with the increase in market fragmentation, we examine how trade processes within the options market influence the structure within options and other financial instruments. The three essays herein use transaction-level options data to investigate the impact of different aspects of options on financial market outcomes.

The next chapter proposes an implied volatility index for the Turkish equities market, namely Volatility of Borsa Istanbul (hereafter, VBI). The implied volatility index (VIX) was first introduced for the U.S. market by Chicago Board Options Exchange (CBOE) to measure market volatility as implied by the underlying S&P 100 index option prices. Other countries later introduced implied volatility indexes using the corresponding underlying index. We start by reviewing the methodology of other indexes and then compute VBI by adapting the estimation processes to suit the microstructure of the Turkish options market. Following the computation of VBI, we explore its characteristics, correlation with other domestic and international financial indicators, and its predictive ability of realized volatility. We find that VBI is negatively correlated with its underlying index, and it contains predictive information about future realized volatility even after controlling for past realized volatility. We also find that VBI has a significant correlation with Turkey's financial indicators, as opposed to insignificant relationship with global financial indicators. Moreover, we document the presence of spillover among the U.S. (VIX), the eurozone (V2X) and the Turkish (VBI) markets.

The third chapter of the thesis builds on the literature by exploiting information in index option trades and investigating the channel through which index options impact spot index returns. Indeed, there are two main views on the nature of feedback between option and the underlying stock markets. The information-based view posits that trades of informed investors in the options market drives the options market's predictability of future stock price movements (Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006). According to this view, informed investors prefer to trade in the options market because of the associated lower transaction costs and higher leverage. The hedging-based view, on the other hand, suggests that hedging activities of market makers and liquidity providers lead to the predictability of underlying stock returns by option market trades (Avellaneda and Lipkin, 2003; Hu, 2014). Both views imply that the options market has predictive power over the underlying asset returns, albeit with a difference in the persistence level and the direction of the prediction. The chapter contributes to the literature that investigates the information flow between the equity and derivatives markets. By using options order imbalance to investigate the channel of information flow between options and equities markets, the chapter also contributes to the microstructure literature that examines the predictive power of order imbalance. We find evidence that increased call buying pressure in the options market places the counterparties (market makers and liquidity providers) in a short call position, leading them to simultaneously delta-hedge the short call option exposure with long position in the underlying market. The dynamic hedging leads to a decrease in underlying spot price and lower weekly index return.

The fourth chapter examines the presence of commonality in individual options. Commonality refers to the co-variation between individual firm-level trading activities and the entire market over time. Prior to the study of commonality, empirical literature analyzed trading activity as a single asset phenomenon. This chapter contributes to this evolving literature by examining the presence of commonality in order imbalance in the options market. We investigate and document the presence of commonality in a purely order-driven emerging derivatives market, the Borsa Istanbul (BIST). The main implication of the results is that the order pressure in an option depends on the buy and sell pressure of other listed options. Therefore, it is important for investors to take the level of commonality in the options market into account when trading.

CHAPTER 2

IMPLIED VOLATILITY INDICES: A REVIEW AND EXTENSION IN THE TURKISH CASE

In 1993, Chicago Board Options Exchange (CBOE) introduced the volatility index (VIX) to measure market volatility implied by at-the-money S&P100 Index option prices. The aim was to introduce a forward-looking volatility measure, unlike historical volatility. Since its introduction, it has become a benchmark for the ex-ante volatility in the stock market and is even regarded as the "investor fear gauge" in financial markets (Whaley, 2000).

The original construction of VIX uses the data of S&P100 Index options to compute an average of the Black-Scholes option implied volatility with strike prices close to the current spot index level and maturities interpolated at about one month. In 2003, the CBOE revised the calculation of the VIX due to both theoretical and practical considerations. S&P500 Index replaced S&P100 Index as the underlying asset to represent the equity market better. Furthermore, CBOE also modified the methodology to measure the weighted average of option prices across all strikes at two nearby maturities within a model-free scheme (Carr and Wu, 2006).

Using the new methodology, the CBOE later introduced several other implied volatility indexes with different underlying indexes such as VXN (NASDAQ volatility index), VXD (DJI volatility Index) and RVX (Russell 2000 volatility index). After successful implementation of the new methodology, other exchanges around the world have also created a new series of implied volatility indexes, including VDAX (Germany), VCAC (France), VFTSE (UK), etc.[1]

Although the construction of this new methodology is straightforward, its empirical estimation is not. The reason behind this is the free selection of several empirical parameters and rules such as the calculation frequency, reference option prices, forward price levels, risk-free rates, option filters and roll-over times. In this study, we first show how this index is constructed in theory and review its estimation process for the most popular ones worldwide. Then, we try to construct the index for one of the leading emerging markets, Turkey. At the moment, Turkey does not have an official implied volatility index. In order to construct the index, we adapt the parameter selection process to suit the Turkish derivatives market microstructure. The main characteristics of the Turkish options market are significantly different from those of the developed markets under consideration, primarily due to options market illiquidity. After constructing the implied volatility index, we examine its time series characteristics, its contemporaneous and lagged relation with domestic and global financial indicators, and whether it adds value to realized volatility forecasting.

Our study is in line with the works by Siriopoulos and Fassas (2012) and Bugge et al. (2016), which introduce the implied volatility indexes for the Greek and the Norwegian stock markets, respectively, using the new CBOE methodology. Siriopoulos and Fassas (2012) show that Greek implied volatility is negatively correlated with its underlying index, and it contains information about future realized volatility. Moreover, they show a unidirectional implied volatility transmission from German and U.S. stock markets to the Greek stock market. Bugge et al. (2016) compare Norwegian implied volatility to VIX and VDAX and show that it

[1]The list of the most popular implied volatility indexes calculated using the new VIX methodology is in the Appendix.

has similar characteristics with the latter two. Similar to the findings of Siriopoulos and Fassas (2012), they also show that the Norwegian implied volatility index significantly improves forecasting of future realized volatility.[2]

This chapter finds that the constructed Turkish implied volatility index (VBI) improves forecasting of future realized volatility.[3] Even after controlling for past realized volatility, it still has strong explanatory power. Analyzing its contemporaneous relation with several financial variables shows us that VBI is significantly correlated with Turkey's financial indicators with the expected sign of correlations. In contrast, this significance mostly disappears when we consider global financial indicators. Further, we investigate the implied volatility spillovers among the U.S., eurozone and Turkish equity markets as proxied by VIX, V2X and VBI, respectively. Accordingly, shocks to the VIX have unidirectional significant spillover effects on the implied volatilities of the eurozone and Turkish equity markets in the same direction. Interestingly, V2X has no such significant effect on VBI. Finally, shocks to the VBI has no significant effect on other implied volatilities as expected.

The rest of the chapter is as follows: Section 2.1 explains how VIX is constructed in theory and presents the differences in estimation procedures across several exchanges around the world. Section 2.2 suggests the ideal parameters to estimate the implied volatility index of Borsa Istanbul. Section 2.3 describes the data and contains the main empirical analysis. Finally, Section 2.4 concludes.

2.1. Construction and Estimation of the New VIX

This section presents the theoretical methodology used to construct VIX and the parameters needed to estimate VIX empirically.

[2]See also the works by Tzang et al. (2011) and Gonzalez-Perez and Novales (2011) for the introduction of implied volatility indexes for Taiwan and Spain, respectively.

[3]VBI stands for the "Volatility of Borsa Istanbul".

2.1.1. Construction

As stated by the Gonzalez-Perez and Novales (2003), new VIX depends on the following formula

$$\sigma^2 = -\frac{1}{T}\left(\frac{F}{K_0} - 1\right)^2 + \frac{2}{T}\left[\sum_{i=1}^{n} \frac{\delta K_i}{K_i^2} e^{RT} Q(K_i)\right] \tag{2.1}$$

then the implied volatility of an option chain is equal to σ, where T is time to expiration, F is forward index level, K_0 is the first strike below the forward index level, K_i is the strike price of the i^{th} out-of-the-money option (a call K_i if $K_i > K_0$ and a put if $K_i < K_0$; both put and call if $K_i = K_0$), δK_i is the interval between strike prices-half the difference between the strike on either side of K_i given by the following:

$$\delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$$

Note that δK for the lowest strike is the difference between the lowest strike and the next higher strike. Similarly, δK for the highest strike is the difference between the highest strike and the next lower strike. Finally, R is the risk-free rate to expiration and $Q(K_i)$ is the option price with strike K_i.

Formula in Eq.(2.1) is applied to near-term (options with closest time to maturity) and next-term (options with closest maturity following near option series) options to get the σ_1^2 and σ_2^2 respectively. Then, σ_1^2 and σ_2^2 are weighted (interpolated) using time to expirations T_1 and T_2 to get a single parameter $\widetilde{\sigma}^2$. Finally, the model-free implied volatility index VIX is calculated as $100 \times \widetilde{\sigma}$.

2.1.2. Parameter Selection

Although the methodology behind VIX has been highly standardized, some deviations naturally arise from institutional features, liquidity concerns or historical conventions. In this part, we document these differences and their reasonings.[4]

Option price $Q(K_i)$ and index calculation frequency

There are various alternatives at this stage, including but not limited to (i) mid-point of the bid-ask price of the last quote on options; (ii) last trade price; (iii) average of all trading prices, and (iv) settlement price as a proxy for the $Q(K_i)$. For example, CBOE uses mid-quote prices, whereas the implied volatility index of Korea (VKOSPI) uses the last trading price. Although, it is not a strict rule to use only one of the methods above. For instance, the Japanese exchange relies on the nature of data available to decide on the alternative to use in the computation of VXJ.

In this selection, there are three potential advantages for the use of mid-quote prices over realized trading prices (Areal, 2008). First, a trade originated by a bid (ask) quote following a trade originated by an ask (bid) quote might create jumps in the option prices. Thus, using mid-quotes reduces this bouncing. Second, there is more data on quotes than trades; therefore, the quote dataset will reflect more information than the trade dataset. This is especially important if the index is to be estimated at a high frequency. Third, the next term's option chain might suffer from illiquidity in terms of trades; however, the order book has more liquidity in terms of order updates. Thus, the order book contains information not reflected in the traded prices; hence using mid-quote prices reduces the effect of missing data.

The methods above are frequently used for the liquid options markets and the corresponding indexes are calculated frequently within the day (ranging from a few seconds to a few minutes). However, it is clear that they would not work when

[4] We collect the technical information presented in this sub-section from the white papers prepared by the indexes. These documents are available for download on the stock exchanges' websites.

the options market suffers from illiquidity in terms of both trades and quotations. In that case, one of the first things to consider is the estimation frequency. In such an illiquid market, it is possible that frequent intraday estimations might not be realized. One can think of using the last known option prices (or quotes) until the new data is available (as in the case of Hong Kong - VHSI), bearing in mind that the index might be stale for a very long time. In order to prevent having a stale index for a long time, one can impose a limit on the duration of inactivity or use cubic splines to curve-fit the option prices for artificial option pricing, as is the case in India (NIFVIX).

Serious illiquidity concerns lead Siriopoulos and Fassas (2012) to estimate the Greek implied volatility index at a daily frequency and to use end-of-day settlement prices for the option prices. The advantage is that a settlement price is calculated based on an algorithm (in particular, a weighted average) and are less prone to manipulation or imprecision. Moreover, whether there is no trade or a quote on a given day, settlement prices still have to be calculated and disseminated by the stock exchange since they are used in marked-to-market margin level calculations.

Forward index price F

A few alternatives also exist at this stage. For example, CBOE determines the forward index level by using the put-call parity for at-the-money strike. However, this approach is accurate and robust only if the measurement errors for the quote midpoint of the at-the-money options are small and the quotes are current. Instead, a broader set of put-call option pairs may be used to determine the forward rate in a more robust, albeit also less precise manner, as noted in the Eurex regulations (Andersen et al., 2015). At this stage, an interesting approach comes from the Indian stock exchange in which they use observed futures prices for the underlying asset in place of the forward price. The exchange states that they have an actively traded, huge and liquid index futures market. Therefore they consider the latest available trade price of the NIFTY futures of the respective expiry month as the forward index price.

Risk-free rate R

The risk-free rate is the theoretical return rate of an investment with zero risk. In the implied volatility index estimations, this rate is used for discounting the option pay-offs. CBOE interpolates these rates from U.S. Treasury bill rates. On the other hand, several others rely on interbank rates, which reflect the costs of unsecured borrowing for major financial institutions. For a liquid bond market, weighting the treasury bill rates works well. However, if the market is illiquid, interpolated rates could be misleading. In such cases, using the interbank rates seems like the better choice because banks give big amounts of loans to each other frequently, and this rate is announced daily in the interbank market.

Since VIX methodology is mostly applied for shorter maturities (30 days), this difference has a negligible impact. However, for volatility indexes covering longer maturities and during periods of financial stress with a high gap between interbank and treasury rates, the difference can become meaningful (Andersen et al., 2015).

Range of strike prices K_i

Not all options are included in the VIX estimation and certain cut-offs are employed to obtain realistic values. CBOE applies a strict stopping rule centered on the at-the-money strike; moving into the out-of-the-money region, all options with positive bid quotes are included until two consecutive zero bid quotes are encountered, after which all further out-of-the-money options are excluded. This process alleviates the noise stemming from low-priced and illiquid options, but it also induces randomness in the effective strike range (Andersen et al., 2015). In practice, employing this rule in an illiquid options market is almost impossible.

Alternatively, Eurex eliminates options with a mid-quote below euro 0.5. In contrast, Hong Kong uses only out-of-the-money options with exercise prices within 20% of the at-the-money strike price, an example of a very inflexible corridor implied volatility index. For other exchanges with the illiquid options market, all quoted options are allowed to contribute.[5]

Option filters

If an exchange has strict restrictions on the range of strike prices, then they typically apply only soft additional filtering rules. For example, the only additional constraint by the CBOE is the exclusion of any remaining options with a zero bid quote. Eurex imposes a maximum spread rule that forces the quotation levels within a practical valid range Andersen et al. (2015).

On the contrary, some exchanges allow all options to enter the index computation but indirectly eliminate illiquid or low-priced options using a maximum percentage spread rule to induce random variation in the option price range. For example, the Hong Kong stock exchange stipulates that the ask quote can not be lower than the bid quote. The remaining differences are primarily due to institutional features.

Roll-over times

In the U.S. market, every month is an expiry month for index options. CBOE uses put and call options in the nearest and next-nearest expiration months to capture a 30-day calendar period. When those options have 8 days until expiration,

[5] According to Wu and Liu (2018), letting the strike prices span the full range might bring estimation errors in VIX. They propose a way to estimate the resulting truncation error using corridor variance swaps. Grover and Thomas (2012) also proposes alternative adjusting schemes. In the case of using settlement prices instead of trade prices or mid-quotations as a proxy for $Q(K_i)$, these approaches become of less interest.

estimations are rolled to the next second and third contract months to minimize pricing anomalies that might occur close to expiration.

Up to this point, we have pointed out that option liquidity is essential to estimate implied volatility properly, and a common problem of emerging options markets is the illiquid trade for the second-nearby month options, not to mention the third-nearby month options. In practice, active trades are primarily conducted on nearby month options. The trades of the second-nearby month options become active only when nearby options are very close to expiry. If next-nearby month options are too illiquid, the estimation errors due to structural noises could be amplified in the case that the roll-over times are long (Tzang et al., 2011).

Indian and Hong Kong stock exchanges roll-over when there are three trading days till expiry. In comparison, the Australian stock exchange prefers five calendar days until expiry, and the Korean exchange prefers four business days till expiry. Gonzalez-Perez and Novales (2011) suggest using three calendar days for a theoretical Spain VIX. For the Greek market, which is an illiquid options market, Siriopoulos and Fassas (2012) suggest using options of the first month until the very last day of their life. Altogether, the literature suggests that roll-over times should be short as liquidity reduces.

Finally, we end this part with a summary of the explanations as mentioned earlier. Table 2.1 presents various implied volatility indexes across the world and the main differences in their calculations.

2.2. Model Suggestion for Borsa Istanbul

In this section, we provide suggestions for parameter selection to estimate the implied volatility index for Borsa Istanbul (hereafter VBI). Options Market of Borsa Istanbul was launched on December 21, 2012, and only individual stocks were traded initially. In August 2013, the product range widened to include options written on the benchmark index, BIST30. Trading is done on a multiple price,

Table 2.1: Main differences in the estimation of popular implied volatility indexes

Country/Exchange	Forward Index F	Risk-free R	Range of Strike Prices K_i	Option Remove Filter	Roll-over Times
CBOE	Cond. (1)	Cond. (2)	Cond. (3)	Cond. (4)	8 calendar days
Canada	Cond. (1)	CORRA/CDOR	Cond. (3)	Cond. (4)	5 calendar days
Germany	Cond. (1.1)	EONIA/EURIBOR	min(Q)	Cond. (4), A=0, MS	2 calendar days
Switzerland	Cond. (1.1)	LIBOR	min(Q)	Cond. (4), A=0, MS	2 calendar days
Eurex	Cond. (1.1)	EONIA/EURIBOR	min(Q)	Cond. (4), A=0, MS	2 calendar days
Euronext	Cond. (1.1)	LIBOR/EURIBOR	All Allowed	Cond. (4), RS>50%	NA
Australia	Cond. (1)	RBA BBSW	All Allowed	Cond. (4)	NA
Hong Kong	Cond. (1)	HIBOR	$[0.8K_0, 1.2K_0]$	Cond. (4), B≥A	3 trading days
India	Index Futures	NSE MIBOR	All Allowed	Cond. (4), RS>30%	3 trading days

Note: Conditions (1) - (4) and the other restrictions are defined as the following:
Condition (1): $F_i = K_i{}^* + e^{R_i T_i} \times |C(K_i{}^*, T_i) - P(K_i{}^*, T_i)|$ where F_i is the forward index price for the i^{th} nearby maturity, $K_i{}^*$ is at-the-money strike price, R_i is the annualized risk-free rate, T_i is time to maturity in years, and $C(K_i{}^*, T_i)$ and $P(K_i{}^*, T_i)$ are the prices of the at-the-money call and put options with maturity T_i respectively. CBOE defines at-the-money strike level as the one which minimizes the distance between the call and put price.
Condition (1.1): This is equivalent to Condition (1), but with the additional condition that "if a clear minimum does not exist, the average of the relevant forward prices will be used instead" to determine F_i.
Condition (2): The annualized yield of the Treasury bill/bond maturing closest to the expiration dates of the relevant options.
Condition (3): Let the out-of-the-money put (call) options be sorted in descending (ascending) order according to strike price. The minimum (maximum) strike $K_{\min}$ ($K_{\max}$) is the out-of-the-money put (call) strike closest to K^* for which the next two consecutive strikes, representing further out-of-the-money put (call) options, have zero bid quotes.
Condition (4): Delete any remaining out-of-the-money options with zero bid prices.
min(Q) Rule: The price of the out-of-the-money option is denoted by $Q(K,T) = \min[C(K,T), P(K,T)]$, and the symbol "min($Q$)" refers to an existence of minimum option price rule for inclusion in the computation.
RS Rule: This rule indicates that relative spread defined by $\frac{A-B}{(A+B)/2}$, with A and B are the best ask and bid levels respectively, can not exceed a certain threshold level.
MS Rule: This rule indicates that maximum spread $|A - B|$ can not exceed a certain threshold level.

continuous auction method in which the orders match automatically based on a price-time priority.

The last trading days of February, April, June, August, October and December are the expiry dates. Contracts with three different nearest maturity dates to the current month are available for trading. If December is not one of those expiration dates, the exchange launches an extra contract with an expiration of December. As evident from these maturity months, we set VBI to measure the implied volatility of the 60-day ahead calendar period, unlike many others.

Our sample period to estimate VBI spans the trading days between October 1, 2013, and February 28, 2017. During this period, the index options market has been relatively illiquid. On some days, there are few trades, and in some cases, bid-ask quotes are not available for an adequate number of strike prices. Therefore, we select our proxies considering this scenario.[6]

- *Option Prices $Q(K_i)$ and index calculation frequency*: VBI is calculated once at the end of the day using the settlement prices officially announced daily by the stock exchange after the trading period.

- *Forward index price F*: The index futures market of Borsa Istanbul is highly liquid.[7] Therefore, the last trade price of the BIST30 index futures contract with the same maturity date of the corresponding index option is a good proxy for the forward index price on a given day.

[6]Indeed, for an implied volatility index to be accurate, the options market is desired to have at least a certain amount of liquidity. When CBOE first introduced VIX, there was already an active and highly developed index options market in the U.S. for almost ten years. For example, Korea introduced index options in 1997 but launched the corresponding implied volatility index in 2009. Similar situations are also observed in India (option introduction: 2000 - index launch: 2008), Taiwan (option introduction: 2001 - index launch: 2006) and Russia (option introduction: 2005 - index launch: 2010).

[7]According to the World Federation of Exchanges, BIST30 Index Futures is the 8th most liquid index futures contracts in the world. For further information, see `http://www.world-exchanges.org/home/index.php/news/world-exchange-news/wfe-ioma-releases-2015-derivatives-market-survey`

- *Risk-free rate R*: At this stage, we prefer the interbank rates (TRIBOR). The main reason is that its alternative, the weighted treasury bond rates, is not very suitable. Although such treasuries are traded on Borsa Istanbul, the average number of trades in a given day is meagre. Notwithstanding, the average daily trade volume is moderate by international standards. On the other hand, Turkey has a very active interbank lending market that is suitable for selection as the risk-free return.

- *Range of strike prices K_i*: Since we use the settlement prices, we do not have any concern about the availability of the quotes or the quotation prices. Therefore, all options are allowed to contribute.[8]

- *Option filters*: Similar to the previous reasoning, all options are allowed to contribute.

- *Roll-over times*: Our empirical analysis shows that on more than 90% of the sample days, most actively traded options are the ones with the nearest time to maturity. Even on the day of the expiry, this observation does not change. Therefore, we use options with the closest maturity until the very last day of their trading life.

2.3. Data and Empirical Results

As mentioned earlier, our sample covers the period between October 1, 2013, and February 28, 2017. All data related to Borsa Istanbul (options, futures, underlying index, Etc.) comes directly from the stock exchange's database. We obtain the rest of the variables from the Bloomberg database.

First, we start by displaying the time-series behaviour of the VBI in Figure 2.1. This figure displays the actual VBI series and the smoothed trend component of the

[8] On each day, Borsa Istanbul introduces index options with strike prices limited from below and above by ±20% of the last trading day's settlement price. So, in practice, we are implicitly using a similar version of the range rule by the Hong Kong Stock Exchange (see Table 2.1).

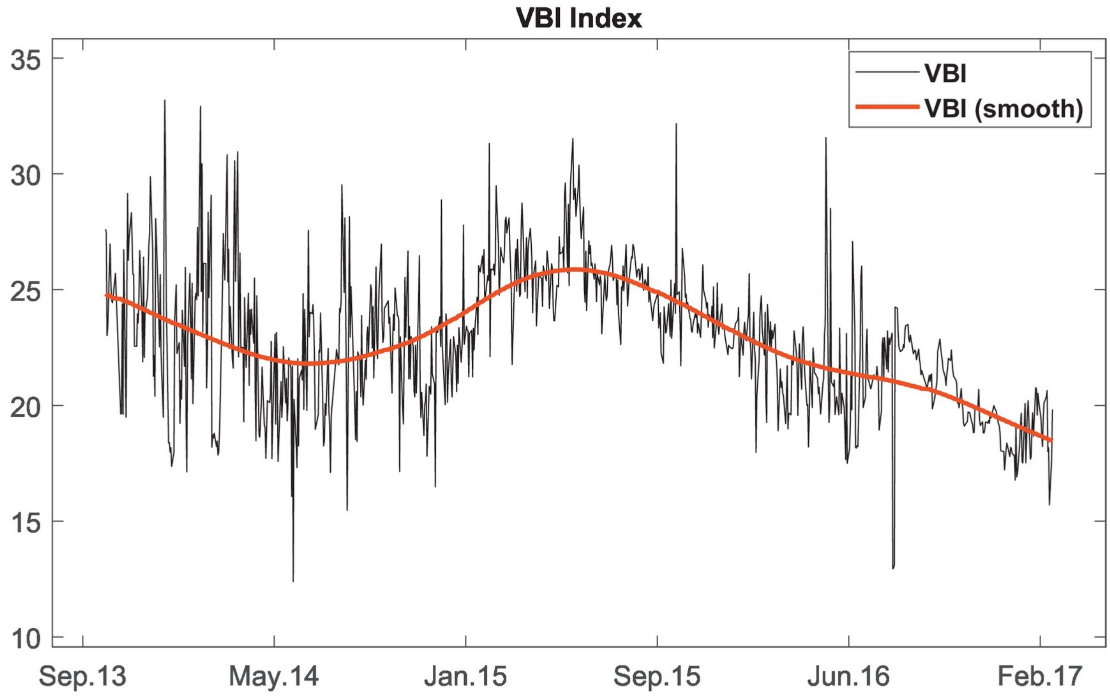

Figure 2.1: Implied volatility index of Borsa Istanbul (VBI) between October 2013 and February 2017. Black curve denotes the actual series while the red curve is the smoothed trend obtained by Hodrick-Prescott filter.

VBI obtained via Hodrick and Prescott (1997) filter, which helps us to eliminate noise and focus on the big picture.[9] The filtered series shows that VBI follows a short cyclical pattern from the end of 2013 till early 2016, taking values between 20 to 25. However, by mid-2016, this pattern was broken, and VBI followed a declining trend until the end of our sample period, reaching values below 20.

2.3.1. Descriptive Analysis of the VBI

Table 2.2 gives us the main descriptive statistics of the VBI level series and its daily changes calculated as $\ln(VBI_t) - \ln(VBI_{t-1})$. According to Panel A of Table 2.2,

[9]The idea of the H-P filter is the following: Let y_t for $t = 1, 2, \dots, T$ denote the logarithms of a time series variable. The series y_t is made up of a trend component, denoted by τ and noise c such that $y_t = \tau_t + c_t$. Given an adequately chosen positive λ, there is a trend component that solves $\min_\tau(\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda\sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2)$. The first term of the equation is the sum of the squared deviations $d_t = y_t - \tau_t$ which penalizes the noise. The second term is a multiple λ of the sum of the squares of the trend component's second differences. This second term penalizes variations in the growth rate of the trend component.

the average daily VBI level and return values are 22.79 and -0.04%, respectively, showing that VBI tends to decrease in our sample period. VBI ranges from a minimum of 12.39 up to a maximum of 33.18, with a daily standard deviation of 3.07. On the other hand, daily VBI returns have seen a maximum and minimum of 61% and 58%, respectively, showing that VBI can change widely in consecutive days. This is further validated by its high unconditional standard deviation of 0.11. Both levels and returns are positively skewed, whereas VBI returns exhibit a relatively high kurtosis of 7.81, compared to the kurtosis value of VBI levels, which is 3.14. Skewness and kurtosis coefficients indicate that return series are not normally distributed, which is also shown by the Jarque-Bera test (JB) that rejects the null hypothesis of normality for the daily return series at 1% significance level. However, the same can not be said for the VBI level series itself.

Table 2.2: Descriptive properties of the VBI

PANEL A: Descriptive statistics of VBI level and return series

	Mean	Median	Max	Min	Std	Kurtosis	Skewness	JB-Test	ADF-Test	KPSS-Test
VBI Level	22.79	22.87	33.18	12.39	3.07	3.14	0.14	3.61	-1.52	5.82***
VBI Returns	-0.04%	-0.15%	61.48%	-58%	0.11	7.81	0.13	828***	-46***	0.002

PANEL B: Time-series characteristics of the daily VBI returns series

	Q(1)-Test	Q(5)-Test	Q(10)-Test	ARCH(1)-Test	ARCH(5)-Test	ARCH(10)-Test
VBI Returns	152***	169***	180***	62***	102***	104***

This table presents the descriptive statistics for the daily VBI level and return series (Panel A) and time-series characteristics of the daily VBI return series (Panel B). The null hypothesis of the Jarque-Berra (JB) test is that series is normally distributed. The null hypothesis of the Augmented Dicky-Fuller (ADF) test is the existence of a unit root. The null hypothesis of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is the stationarity of the time-series. The null hypothesis of the Ljung-Box Q test is that returns are not autocorrelated. The null hypothesis of the ARCH-LM test is the absence of the ARCH effect. In both panels, *, ** and *** denote 10%, 5% and 1% significance level.

Panel A of Table 2.2 also presents the results of the conventional stationarity tests for the VBI level and return series (unit root tests contain a constant). Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of unit root for the return series at the 1% significance level. Similarly, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test can not reject the stationarity of the VBI returns. On the contrary, both tests found that the VBI level series is non-stationary, as expected.

Further, we examine the existence of serial correlation and heteroskedasticity in returns via Ljung-Box Q-test and ARCH-LM test, respectively, using lags from 1 to 10. Accordingly, the return series exhibit the ARCH behaviour and is serially correlated like many other financial return series.

2.3.2. Forecasting realized volatility

One of the main concerns regarding the implied volatility indexes is whether they add value to forecasting future realized volatility or not. In this section, we try to answer this question.

VBI aims to reflect the 60 calendar days ahead realized volatility (RV) which is estimated in the following way:

$$RV_{t+60} = \sqrt{\frac{30}{22} \times \frac{252}{43} \times \sum_{i=1}^{44} (r_{t+i} - \frac{1}{44} \sum_{j=1}^{44} r_{t+j})^2} \tag{2.2}$$

In this representation, r_t is the equity index return on day t, $\sqrt{30/22}$ is an adjustment factor that makes return volatility conform to the same 22-trading-day basis to which VBI is calibrated.

To start with, we present Figure 2.2 to show how these two variables are related. A rough look at Figure 2.2 shows that, except for the spikes in future realized volatility around October-November 2013 and May-June 2016, the two variables seem to be highly consistently correlated with each other.[10]

[10]The two spikes in future realized volatility can be explained as follows: First, during December 17-25, 2013, Turkey was confronted with a corruption investigation that caused a ripple in the political scene. The investigation involved several key people in the Turkish government, family members of cabinet ministers and various people in business. Second, on July 15th, 2016, there was an attempted coup d'état in Turkey. Both events created severe turmoil in the Turkish equity market, echoing for weeks. Since they could not be anticipated prior to their occurrences by the market participants, the difference between implied volatility and future realized volatility widens in the relevant periods.

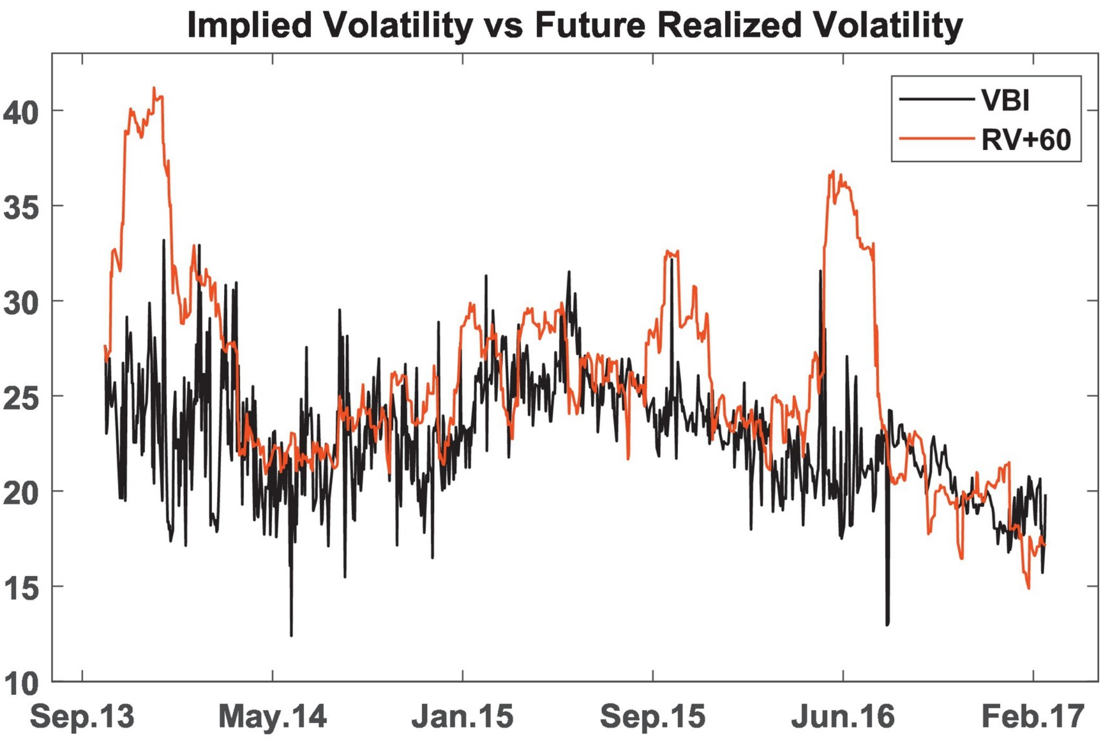

Figure 2.2: Implied volatility vs realized volatility in the next 60 calendar (44 trading) days.

We then estimate the following Equations (2.3) and (2.4).[11]

$$\ln(RV_{t+60}) = \alpha + \beta_1 \ln(VBI_t) + \varepsilon_t \tag{2.3}$$

$$\ln(RV_{t+60}) = \alpha + \beta_1 \ln(VBI_t) + \beta_2 \ln(RV_t) + \varepsilon_t \tag{2.4}$$

According to Christensen and Prabhala (1998), if VBI contains at least some information about future realized volatility, coefficient β_1 in Equation (2.3) should be statistically significant. Furthermore, the significance should be preserved even after we control for the past realized volatility as in Equation (2.4). The estimations of these equations are performed via iteratively re-weighted least squares with a bisquare weighting function to get robust statistics, and the results are given in Table 2.3.

[11]The natural log-transformation of variables in these equations are performed to get stationary series.

Table 2.3: Realized volatility forecasting power of VBI

	α	β_1	β_2
Equation (2.3)	1.3137***	0.6095***	-
	(9.823)	(14.218)	-
Equation (2.4)	0.6721***	0.4344***	0.3562***
	(4.872)	(10.357)	(10.192)

In this Table, Equation (2.3) stands for $\ln(RV_{t+60}) = \alpha + \beta_1 \ln(VBI_t) + \varepsilon_t$ whereas Equation (2.4) represents $\ln(RV_{t+60}) = \alpha + \beta_1 \ln(VBI_t) + \beta_2 \ln(RV_t) + \varepsilon_t$. Estimations are performed via iteratively re-weighted least squares with a bisquare weighting function. The values in the parentheses are t-stats. *** denotes 1% significance level.

Results for Equation (2.3) show that implied volatility as proxied by VBI contains essential information regarding future realized volatility since its estimated coefficient is 0.61 and is highly significant. Accordingly, a higher (lower) implied volatility today implies a higher (lower) realized volatility within the next 60 calendar days in the equity market of Borsa Istanbul.

Moreover, the results for Equation (2.4) indicate that: (i) volatility is persistent since the lagged realized volatility is significant, and (ii) implied volatility can still explain future realized volatility even when we take the past realized volatility into account. In this specification, the coefficient of VBI slightly decreases from 0.61 to 0.43 with a slight loss of significance. Nevertheless, it still has a more substantial explanatory power than the past realized volatility in coefficient magnitude and significance.[12]

To support the argument above, we further estimate the root mean square errors (RMSE) when VBI and historical realized volatility are separately used to predict future realized volatility. In this setup, we compute RMSE as the following:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (\hat{y}_t - y_t)^2}{N}} \tag{2.5}$$

[12] At this stage, it would be possible to use more advanced techniques, but we wanted to make the results clear for the general audience and also make it comparable to the previous studies.

where $\hat{y}_t$ is the 60 calendar days ahead realized volatility on day t. In the first case, we take y_t to be the VBI level on the day t, and in the second case, y_t is taken to be the realized volatility in the past 60 calendar days (which is known as the *naive* case). According to these assumptions, RMSE values are 5.82 and 5.94 for VBI and historical volatility, respectively, where the former value is significantly lower than the latter. This finding and the results in Table 2.3 show the superiority of our implied volatility index VBI over the past realized volatility in forecasting the future realized volatility of the Turkish market. Furthermore, employing the modified version of RMSE given in Eq.(2.6) shows that using the implied volatility and the past realized volatility together improves the forecasting results significantly. In this setup, the α that minimizes the Eq.(2.6) is found to be 0.5149 leading to an $RMSE(\alpha)$ value of 4.82, which is significantly smaller than both of the previous individual scores.

$$RMSE(\alpha) = \sqrt{\frac{\sum_{t=1}^{N}(RV_{t+60} - \alpha \times VBI_t - (1-\alpha) \times RV_t)^2}{N}} \tag{2.6}$$

2.3.3. Relation with the domestic and global financial indicators

In this section, we examine the relationship between VBI and major domestic and global financial indicators. For this purpose, we consider the daily data of the following as the domestic/country-related variables: (*a*) BIST30 Equity Index, (*b*) local currency government bond yields with 10 years to maturity (TR10Y YIELD), (*c*) equally weighted Euro-USD basket value against Turkish Lira (FX BASKET), (*d*) CDS written on USD denominated Turkish sovereign bonds with 5 years to maturity. For the global financial indicators, we select: (*e*) Brent crude oil, (*f*) gold, (*g*) yield of U.S. treasuries with 10 years to maturity (US10Y YIELD), (*h*) MSCI World stock market index, (*i*) financial conditions of the U.S. (FCON US),

(j) financial conditions of the eurozone (FCON EU), (k) implied volatility index of the U.S. (VIX), and (l) implied volatility index of the eurozone (V2X). All data are obtained from Bloomberg.

For further examination, we analyse the correlations between daily changes in VBI and the other variables. For all indicators except financial conditions, we use log-returns to measure daily changes. Since financial conditions indexes might take negative values, we use first differences for those variables.

The first row in Panel A of Table 2.4 presents the unconditional correlation values between VBI and the domestic indicators. Accordingly, VBI is negatively correlated with the underlying equity index. The correlation between the two is -0.118 and significant at 1% level. This result implies that VBI can provide diversification benefits and is consistent with the results in the literature.[13] Qualitatively, this negative correlation is consistent with the earlier works on this subject (Whaley, 2000; Simon, 2003; Giot, 2005; Bollerslev et al., 2006; Hibbert et al., 2008). However, the correlation level in our case is relatively low compared to the findings of others. Indeed, (Bugge et al., 2016) face a similar situation when they construct the implied volatility index for the Norwegian equity market. They attribute the results to the lack of options market liquidity in the Norwegian market. Due to this illiquidity problem, the implied volatility index can not absorb information very well, and the diversification benefits of implied volatility index against corresponding equity index is limited.

Besides the equity market index, VBI is significantly and positively correlated with the country related financial indicators. Although the correlation levels are low, they indicate a positive contemporaneous relation between VBI and FX, CDS, and bond markets. This is an expected property of an "investor fear gauge" in an emerging market. Emerging markets are infamous for their currency and debt

[13] In addition to the diversification benefits created by this situation, Black (2006) suggests that the skew and excess kurtosis of many hedge fund strategies can be eliminated by a small long exposure to spot implied volatility index.

Table 2.4: Unconditional and conditional correlations between VBI and major financial indicators

PANEL A: Correlations with Turkey related financial indicators

	BIST30	FX	CDS	TR10Y Yield
VBI (uncond.)	-0.118***	0.061*	0.056*	0.085**
p-value	0.001	0.081	0.090	0.013
VBI (cond.)	-0.128***	0.073*	0.087*	0.111***
p-value	0.001	0.075	0.062	0.009

PANEL B: Correlations with global financial indicators

	Crude Oil	Gold	MSCI World	US10Y Yield	FCON US	FCON EU	VIX	V2X
VBI (uncond.)	-0.044	-0.045	-0.076**	-0.017	-0.017	-0.064*	0.021	0.051
p-value	0.197	0.193	0.027	0.624	0.615	0.061	0.552	0.142
VBI (cond.)	-0.051	-0.038	-0.081**	-0.037	-0.017	-0.077**	0.016	0.063
p-value	0.176	0.195	0.013	0.566	0.600	0.049	0.633	0.111

Note: *, ** and *** denote 10%, 5% and 1% significance level in both panels.

crisis, and Turkey is no exception. When such crises occur, we observe massive capital outflows leading to depreciation of the local currency, decrease in bond prices and an increase in the country default risk, all supporting the signs of the correlations mentioned above.

On the other hand, we do not observe significant correlations between VBI and the global financial indicators, except the MSCI World stock market index and the financial conditions of the eurozone (see the first row in Panel B of Table 2.4). The latter shows that as the financial conditions surrounding the eurozone improve (worsen), investor fear in the Turkish equity market decreases (increases). This finding is not surprising as the eurozone is the largest trading partner of Turkey. In addition, equity market investors from eurozone hold more than 20% of the total market capitalization of Borsa Istanbul in their portfolios.[14] Contrarily, a significant negative correlation between VBI and the MSCI index can be explained by the following: Our sample overlaps with the turbulent periods of the eurozone sovereign bond crisis, and in the meantime, Turkey also had specific political problems. Both cases might lead stock market investors in Turkey (and also in other emerging markets) to search for risky alternative assets in the global financial arena. If that is the case, capital outflow from these emerging markets will cause a depreciation in both the benchmark equity indexes and the local currencies against the USD, which would increase the investor fear in these countries, hence a rise in the corresponding implied volatility. If the new investments flow to developed markets such as North America or the U.K., then the MSCI World index would increase due to the relatively larger weights of these developed markets in the calculation of this index. Therefore the correlation would be negative.

It is interesting to see that VBI is not significantly correlated with two of the most important commodities in the world, crude oil and gold. Furthermore, insignificant correlations between VBI and the financial conditions of the U.S., VIX

[14] `https://www.mkk.com.tr/project/MKK/file/content/Bilgi\%20Merkezi\%20Dosyalar\%C4\%B1\%2FBorsa\%20Trendleri\%20Raporu\%2FBorsa\%20Trendleri\%20Raporu\%20XXI`

and V2X present a puzzling case even though their signs are as expected. One reason might be the illiquidity of the options market in Turkey. Accordingly, as argued by Bugge et al. (2016), information can not be captured well by the VBI; hence the correlations remain insignificant. Another argument might be the asynchronicity in the calculation of these variables. VBI is calculated at the end of the day when the Turkish market is closed, whereas U.S. related variables are still traded/calculated at that time. Notwithstanding that the dates are the same, some of the global variables reflect a few hours ahead of information since we use end-of-day data for each variable. Therefore, a lead-lag scheme should be considered, which we will do later in this chapter.

While presenting the descriptive statistics, we showed that daily changes in VBI exhibit powerful ARCH effects, like much other financial return series. One concern may be that the ARCH effect influences the correlation levels and the previous findings are not valid. To deal with this concern, we estimate the conditional correlations between the daily changes in VBI and the other indicators via the constant conditional correlation model of Bollerslev (1990). In doing so, we use a standard GARCH(1,1) model for the univariate volatility of the considered variables.[15] Conditional correlation levels are presented in the third rows in both Panel A and Panel B of Table 2.4. New correlation levels show that not only are the previous findings valid, but they are also more robust in terms of correlation levels and the statistical significance of these correlations. Therefore, the findings are robust.

2.3.4. Implied volatility spillovers

In this part, we examine the spillover effects of the implied volatility of the U.S. equity market, as proxied by VIX, and the implied volatility of the eurozone equity markets, as proxied by V2X, on the implied volatility of the Turkish equity

[15] To save space, we do not report the results of the GARCH estimations here. However, they are available upon request.

Table 2.5: Parameter estimates for the VAR(1) model

	VBI_t		VIX_t		$V2X_t$	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
VBI_{t-1}	-0.420***	-13.53	-0.006	-0.24	-0.023	-1.20
VIX_{t-1}	0.171**	2.28	0.001	0.02	0.276***	8.22
$V2X_{t-1}$	-0.056	-0.85	-0.016	-0.33	-0.219***	-5.48
constant	-0.0006	-0.17	-0.0003	-0.11	-0.0002	-0.08

Note: ** and *** denote 5% and 1% significance level.

market, as proxied by VBI. The bottom right corner of Figure 2.3 presents how these indexes vary during our sample period. As an emerging market, it is natural to observe that the implied volatility level of the Turkish equity market is higher than the other two on average. Indeed, the daily mean value of VBI is 22.77, whereas the mean value is 15.27 and 21.27 for VIX and V2X, respectively. The higher daily mean level of V2X compared to VIX can be explained by the fact that a considerable part of our sample period overlaps with the turmoil of the eurozone sovereign debt crisis.

In order to examine the relationship between implied volatilities of the selected markets, we use the vector autoregressive analysis (VAR(p)) and the generalized impulse response functions (GIRF) on the daily log-returns of VBI, VIX and V2X. Both methodologies are commonly used to capture the dynamic structure of interrelated time series and they suit our use in this case very well. The appropriate lag length of the VAR model is determined by the Bayesian Information Criteria which we found to be 1. The estimated parameters of the VAR model are given in Table 5 and Fig. 4. Fig. 5 display the impulse responses of implied volatilities to the shocks in the system.

According to Table 2.5, VBI is significantly affected both by its lagged values and the VIX, whereas lagged V2X has no such a significant effect on VBI. Accordingly, an increase in VIX today has a significant impact on VBI in the same direction tomorrow. In addition to that, there is no spillover from other implied volatilities

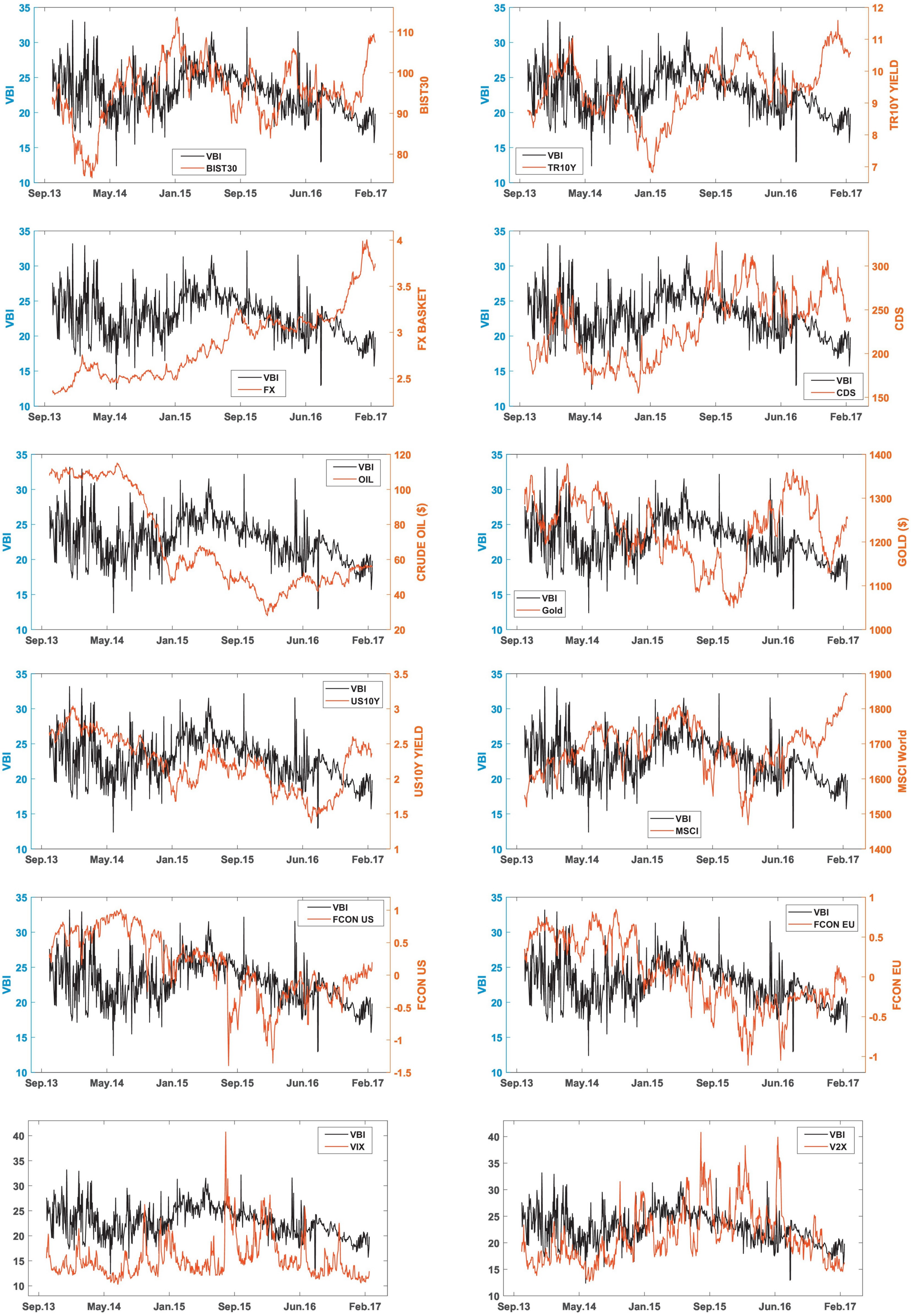

Figure 2.3: VBI and its relation with several domestic and global financial indicators.

to VIX but lagged VIX has a significant positive effect on V2X. As expected, VBI has no significant explanatory power on the changes in the other two indexes.

Similar conclusion can be extracted from the impulse response analysis in Figures 2.4- 2.5. According to Figure 2.4, shocks to the implied volatility of the U.S. equity market has a significant impact on the implied volatility of the Turkish equity market in the same direction, lasting up to 2 days. We do not observe such a significant effect from the eurozone equity markets to the Turkish equity market. On the other hand, Figure 2.5 shows that shocks to VBI has an effect on the implied volatilities in the U.S. and eurozone equity markets. As expected, no significant impact is observed here.[16]

In sub-section 2.3.3, we have shown that the correlation between daily changes in VBI and the financial conditions of the eurozone is significant. However, the same could not be said for the correlation between VBI and the U.S.'s financial conditions and the correlation between VBI and VIX. One of the possible explanations for this case was the asynchronicity between Turkish and the U.S. equity markets. We are using these indexes' daily market closing values; therefore, even though we are on the same calendar day, the U.S. and Turkish data cannot be technically characterized as contemporaneous. On the other hand, this problem is negligible in the case of Turkey and the eurozone since the time difference between the two regions is only 1 hour. VAR and GIRF analysis seem to verify this explanation as the lagged VIX has a significant impact on VBI, whereas lagged V2X has no such significant effect.

[16] A recent study by Sensoy et al. (2014) finds similar results up to some point. In their study, authors construct a financial conditions index for Turkey, and then examines its relation with the financial conditions in U.S. and the eurozone via VAR and GIRF analysis. According to their results, even though financial conditions of both the U.S. and the eurozone have significant impact on the financial conditions of Turkey, the former has a higher effect.

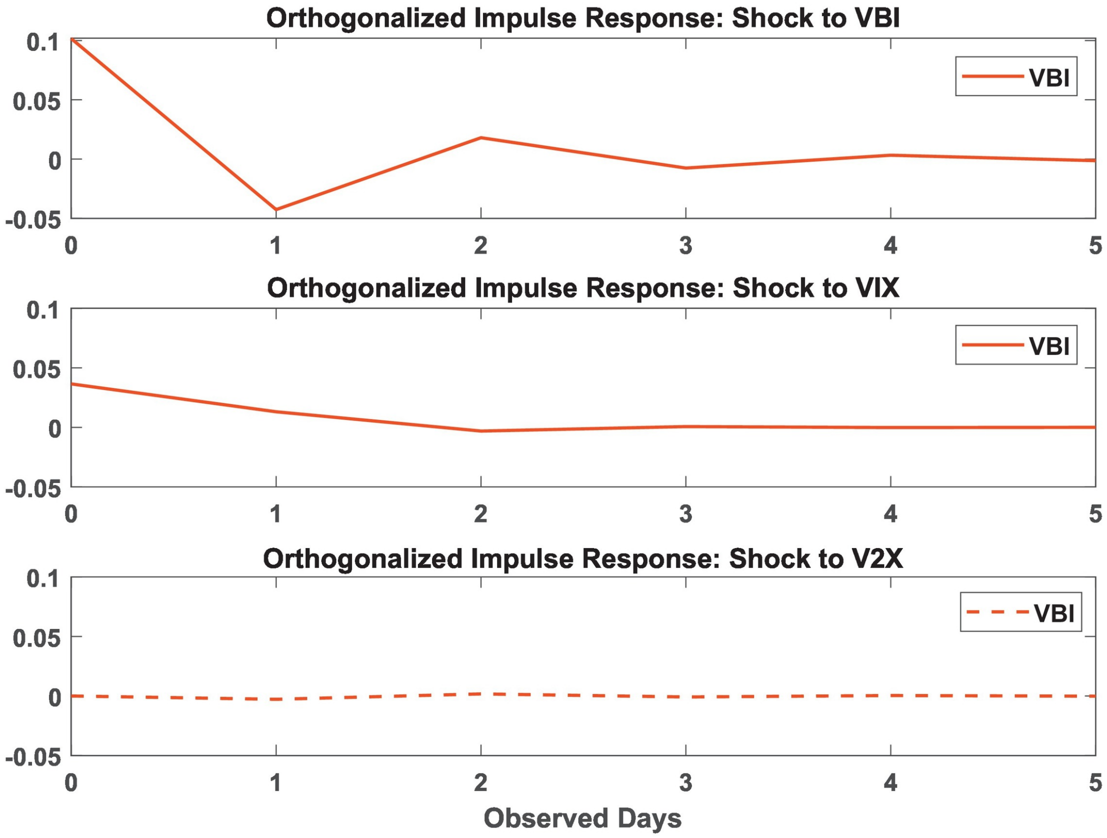

Figure 2.4: Generalized impulse responses of VBI to the shocks. Dashed line denotes insignificance.

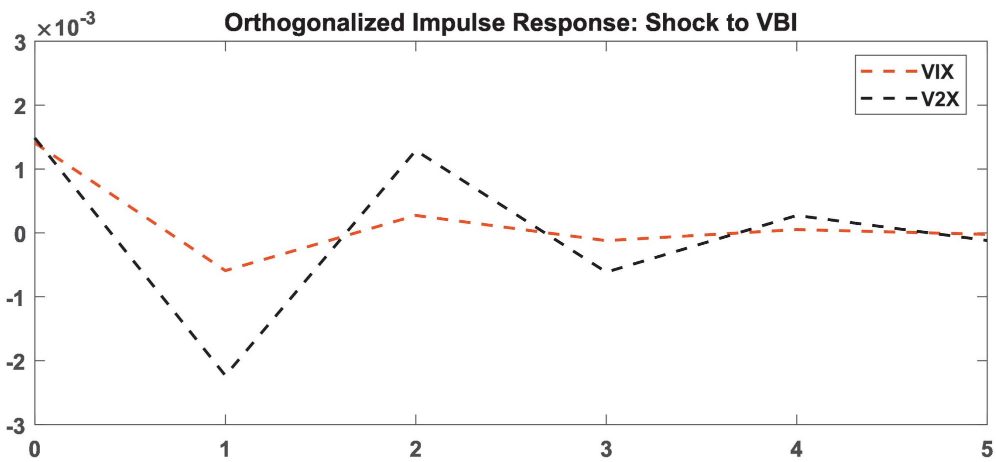

Figure 2.5: Generalized impulse responses of VIX and V2X to the shocks to VBI. Dashed line denotes insignificance.

2.4. Conclusion

We describe the CBOE model-free methodology for constructing the widely popular implied volatility index VIX. Although this methodology is straightforward in theory, it is not straightforward to estimate it empirically because several variables are proxied. Accordingly, one must determine parameters and rules such as the calculation frequency, reference option prices, forward price levels, risk-free rates, option filters and roll-over times.

In this chapter, we first review the popular implied volatility indexes worldwide that use the same CBOE methodology. We give details about their parameter selections along with their reasonings. Then we modify this selection process to make it compatible with an emerging market, Turkey, where the options market is illiquid and immature. Applying this procedure to Borsa Istanbul's data, we introduce VBI, the implied volatility index of the Turkish equity market.

We use VBI to obtain several critical empirical results: First, we show that VBI is a strong predictor of the future realized volatility of the underlying equity index. Even when we control for historical (realized) volatility, the predictive power of VBI remains highly statistically significant. Moreover, compared to historical (realized) volatility, VBI is a stronger predictor both in terms of coefficient magnitude and statistical significance. In addition, using both of them at the same time improves the forecasting process dramatically. Second, we examine the relation between VBI and several important domestic and global financial indicators. We find that VBI is significantly correlated with country related indicators such as Turkish equity market index, foreign exchange rate against Turkish lira, local currency government bond yields, and CDS written on the USD denominated sovereign bonds of Turkey. However, the correlations become insignificant when we consider global financial indicators such as crude oil, gold, U.S. treasuries with 10 years maturity, financial conditions of U.S., and the implied volatilities of U.S. and eurozone equity markets. The only exceptions are the MSCI global stock market index and the financial conditions of eurozone, in which the correlations are both significantly negative. Third, we investigate the implied volatility spillovers among Turkish, U.S. and eurozone equity markets. Vector auto-regression and impulse response analysis reveal that implied volatility spills over from the U.S. equity market to eurozone and Turkish equity markets, but not the other way around. As expected, the Turkish equity market's implied volatility has no spillover effect on the other two markets.

Once the data is available, further research might include estimating the implied volatility index for those emerging markets without official indexes. Implied volatility indexes have been shown to be important tools for investors, policy-makers and academics due to their forward-looking property. Introducing these indexes to a broader range of markets might improve asset and risk management and provide effective policy-making in those countries.

CHAPTER 3

INFORMATION CONTENT OF ORDER IMBALANCE IN THE INDEX OPTIONS MARKET

3.1. Introduction

Finance literature offers several views on the nature of feedback between the options market and the underlying stock market. Black (1975) posits that informed investors who aim to maximize their profits find option market attractive because of lower transaction costs and higher leveraging power. Further, the nature of the options market that allows an asset to have multiple contracts makes it a conducive avenue for agents to hide informed trades. In the model of Easley, O'Hara and Srinivas (1998), market makers assign probabilities to the proportion of informed and uninformed trades in the market. When market makers receive positive (negative) information signals from options trades, they update their beliefs by increasing (decreasing) the bid and ask prices in the stock market. The price adjustments lead to the revelation of informed option trades in the underlying market. Pan and Poteshman (2006) directly test the implications of the model and find empirical support, showing that the predictive power of options volume on future stock prices is contained in the trade of informed investors. Under this information-based view, the options market aids price discovery since trading activity in this market contains information about future price movements of the underlying asset by providing signals about informed investors' expectations.

Another strand of the literature explores how price pressures resulting from hedging activities of market makers can reinforce the predictive effect of options on stock market dynamics. Avellaneda and Lipkin (2003) propose a model that demonstrates how delta-hedging can have an impact on underlying stock prices, particularly around expiry dates. The model predicts that underlying stock prices converge towards options' strike price as delta-hedgers carry out trades that hedge their net option exposures. Ni, Pearson and Poteshman (2005) find that the need for options market makers to re-balance their hedging trades leads to clustering of underlying stock prices around the expiration days. Barbon and Buraschi (2020) provide evidence that delta-hedging activities of market makers contribute to the price formation of the underlying assets. Henderson, Pearson and Wang (2012) empirically test the impact of hedging activities that stem from the issuance of structured equity products (SEP) on the underlying stock. They find that the hedging activities lead to sizable price changes in the underlying. According to Hu (2014), market participants can delta-hedge their options market risk exposure using the stock market. These hedging trades lead to changes in stock order flow, causing temporary stock price pressures, thus affecting stock price movements. We exemplify this dynamic with call options. Call buying pressure in the options market puts counterparties such as market makers and liquidity providers in short call positions. When there is an increase in call buying pressure, the counterparties simultaneously delta-hedge the short call options exposure with long position in the underlying spot market. The hedging demand is reflected as an increase in demand in the stock market, causing the stock order imbalance to increase, leading to an increase in the underlying price. Conversely, suppose there is a net call selling pressure in the market. In that case, the passive investor, the liquidity provider or market maker in the order-driven options market is in a long call option position. The counterparties dynamically hedge the option exposure by short selling the underlying index, decreasing underlying asset price and lowering weekly index return.

Both information-based and hedging-based views imply that the options market has predictive power over the underlying asset returns. However, there is a difference in the direction of the prediction. In the information-based view, faster price discovery drives the prediction. Therefore, the direction of the predictive power of options trades on stock market return is persistent. On the other hand, the hedging-based view predicts that the direction of the predictive power of options trades is temporary as the stock market price pressure induced by hedging trades subsides and leads to return reversals.

The main goal in this chapter is to investigate which of the information-based or hedging-based views hold in a yet to be explored market. To do this, we use index option trading records in a leading emerging market, Turkey, to examine the effect of index options trading volume on contemporaneous and future spot market index movements. We mainly focus on the nature of the predictive relation between index options and the underlying index. Turkish option market structure is different from those of other financial markets commonly explored in the literature. In the quote-driven U.S. market, there are designated market makers and only the bid and ask prices of market makers are revealed. However, in the Turkish order-driven derivatives market, orders are automatically matched at the best bid and ask price, and there is a price-time priority in the trade matching process. All orders (limit and market) are revealed in the order book, and there is a continuous matching of best buy and best sell orders in the system, after which an order turns into a trade. This difference suggests a potentially different informational role for the Turkish index options market.

This study contributes to the literature that investigates the information flow between the equity and derivatives markets. While some studies find that the options market contains information about the stock market dynamics, some find otherwise. The lead-lag relationship between derivatives and stock markets has been a subject of debate in the literature starting from Manaster and Rendleman (1982), who show that end-of-day option trading prices lead stock prices. Later, Easley, O'Hara and Srinivas (1998) develop a pooling equilibrium model in which investors can trade information in both stock and options markets. They find empirical support for the model prediction that shows a contemporaneous and predictive relationship from options volume to stock price changes which they attribute to information related trading. Chakravarty, Gulen and Mayhew (2004) find that options trading enables price discovery in the stock market by providing direct evidence that the former leads the latter. On the other hand, Stephan and Whaley (1990) find evidence that stock price movements lead to changes in option prices. Chan, Chung and Fong (2002) test whether trade volume and price quote returns in both markets have predictive power on each other. They find that stock trades and quotes and options quotes, but not option net trade volume, contain information about changes in the stock market. Their result suggests that informed investors initiate trades in the options market only when the value of information is considerable. More recently, Muravyev, Pearson and Broussard (2013) find that option price quotes do not convey extra information about future stock prices beyond the information reflected in the stock market. The absence of consensus in the literature about the benefits of options instruments in forecasting underlying asset movements leaves the predictive power of the options market as an empirical question that remains unresolved. We employ the vector autoregression model to assess the lead-lag relationship between the stock and options markets.

The second contribution of this study relates to the microstructure literature that examines the predictive power of order imbalance. We use order imbalance in the options market to investigate the channel (informed options trading or delta-hedging trades) of information flow between options to equities markets. According to Chordia and Subrahmanyam (2004), there are at least two reasons why order imbalances can provide additional power beyond the ordinary trading activity measures, such as volume in explaining asset returns. First, a high absolute order imbalance can alter returns as liquidity providers and market makers struggle to re-adjust their inventory. Second, order imbalances can signal excessive investor interest in an asset, and if this interest is persistent, then order imbalances could be related to future returns. Based on these arguments, order imbalance is an important descriptor that allows us to understand the general sentiment and direction the market is headed.[1] For example, Pan and Poteshman (2006) use put-call ratio computed as buyer-initiated put option volume divided by total buyer-initiated option volume as a measure of informed trading in the options market. They find evidence of informed options trading in individual stock options but not in S&P500, S&P100 and NASDAQ100 index options. They claim that it is less likely to find predictive power in index options than individual stock options. However, Chordia, Kurov, Muravyev and Subrahmanyam (2021) recently find market-wide predictive power in S&P500 index put option order imbalance. Schlag and Stoll (2005) find that the DAX index futures market, rather than the DAX options market, is the venue for price discovery in the German DAX index. However, Kang and Park (2008) find evidence of price discovery in the Korean options market, showing that net buying pressure in call and put options contain short term predictive power for the underlying index returns. Li, French and Chen (2017) demonstrate the presence of informational content in SPX options around the 2008 global financial crisis, suggesting that investors use market-wide information to generate profit. The information can either be due to investor access to private information or investors' ability to process public information more accurately. Very recently, Luo, Yu, Qin and Xu (2020) show that single stock options order imbalance can positively and significantly predict daily individual stock returns, and informed trading (rather than the price pressure) better explain this predictability. In our study, we add to the literature mentioned above by examining the relationship between the order imbalance in the index options market and the underlying index returns for Borsa Istanbul, the sole exchange entity of Turkey. Different than Luo, Yu, Qin and Xu (2020), we work at the market-wide index level, not individual equities.

[1] For some of the papers on equity market order imbalance, see Chan and Fong (2000); Chordia, Roll and Subrahmanyam (2002); Chordia and Subrahmanyam (2004); Lee, Liu, Roll and Subrahmanyam (2004); Hvidkjaer (2006); Bailey, Cai, Cheung and Wang (2009) and Yamamoto (2012).

This study finds a contemporaneous positive (negative) effect of call (put) order imbalance on index returns. At the same time, total options volume has no significant relationship with index returns, supporting the notion that total options volume conceals information about the linkage between options and stock markets. Furthermore, we find a negative effect of lagged call order imbalance on index returns. We examine causality relationships between the Turkish spot index and the associated derivatives using the vector autoregression (VAR) model to understand this phenomenon. The model takes the order imbalance of index call and put options, Turkish implied volatility index, macroeconomic indicators into account to examine the short-term dynamics of the relationship and to control for macroeconomic effects in doing so. Supporting the hedging-based view, we find that call order imbalance Granger causes next-week index returns in the negative direction following a contemporaneous positive correlation. On the other hand, we find no evidence of causal linkage from put order imbalance to index returns.

Like the options market, information trades and hedging demands in the futures market can also lead to the transfer of order imbalance to the stock market, resulting in changes in spot prices. In addition, buying pressure specific to the stock market can have an impact on price dynamics. Therefore, we incorporate index futures and market-wide stock order imbalance into the vector autoregression model to account for other markets that investors use to implement their trading strategies. The estimates from the correlation of residuals in the model reveal that a shock to call order imbalance is accompanied by a shock to market-wide equity order imbalance. The causality results show that the main findings still hold that call options and not other contingent claims are the sole predictor of Turkish flagship index returns. This further enhances the interpretation that follows from the hedging-based view that hedging demand of counterparties in the options market leads to increased price pressure in the spot market. This non-fundamental pressure drives the returns that reverse in the following week.

Further analysis in this chapter evaluates the separate impact of positive and negative option order imbalance. The result indicates that the reversal effect of call order imbalance on the next-week index returns is mainly driven by negative call order imbalance. We also test the channel of the predictive power of index options on spot returns in weeks of significant macroeconomic news announcements. In such weeks, the information-based view is likely to hold if informed investors with private information or sophistication to quickly trade newly released public news use the options market to their advantage. However, our results show that the hedging-based view dominates for call options even in weeks of major macroeconomic news. We then use delta-weighted order imbalance in place of total order imbalance to examine the robustness of our results. The guiding intuition is that the higher the delta-weighted option order imbalance, the greater the pressure on counterparties to delta-hedge their options market exposure in the spot market. The result shows that delta-weighted order imbalance has a causal effect on the next-week return negatively, supporting the main results. We also document that innovations to call order imbalance (defined as the change in order imbalance) has a negative causal effect on spot index returns.

Altogether, we conclude from the results in this chapter that the linkage and predictive power of call index options on spot index returns is through the hedging-based view rather than the information-based view. This study is related to Chordia, Kurov, Muravyev and Subrahmanyam (2021) who examine the predictability of market returns from index options trading in the quote-driven U.S. market. In contrast, this study complements earlier studies by focusing on the Turkish market, a leading emerging market economy with different market structures and liquidity. The different liquidity levels and market structure suggest a feedback mechanism between options and the stock market in the Turkish market that is different from the U.S. market, which is the primary focus market in the existing literature. Our findings show that the hedging activities of counterparties drive the feedback effect in the sample market rather than investors' demand for put options as insurance in periods of high market uncertainty. Our study is first to demonstrate a different mechanism in the index options market where the reaction of counterparties to index option trades predict spot market price movements. While both papers find a predictive power in index option trades, this paper demonstrates a different channel, hence the direction, of predictability of index option trades which is likely due to the difference in market structure and liquidity in the sample markets.

The remainder of this paper proceeds as follows. Section 3.2 describes the Turkish option market and the data used in this study. Section 3.3 presents the methodology and provides the main results. Section 3.4 reports the additional tests. Section 3.5 concludes.

3.2. Data and Variables

Our sample market belongs to the Borsa Istanbul Group, the sole exchange entity of Turkey, combining the former Istanbul Stock Exchange, the Istanbul Gold Exchange and the Derivatives Exchange of Turkey. As of the end of the year in 2019, the equity market of Borsa Istanbul has 2,130TL billion annual total traded value (21st in the world) with a share turnover velocity of 227% (3rd in the world). Similarly, its derivatives market has 1,457TL billion total traded value in the same year.[2] These statistics show that sample markets are fairly liquid at a global scale.

We obtain the transaction-level index contingent claims data for this study from the Borsa Istanbul database. The sample data covers all trading days from 1st March 2017 till 30th June 2020. We begin the sample period on 1st March 2017 since it is the first day of Nasdaq's Genium INET trading system operating in the Turkish derivatives market. This system enables the various types of new investors, such as high-frequency traders (HFTs), to join the derivatives market.[3]

[2] https://www.borsaistanbul.com/files/BORSA_IST_IAR2019ENG.pdf

[3] Since HFTs use much different trading algorithms compared to regular investors, including earlier sample periods would cause inconsistency in the data structure. On the other hand, HFTs were already present in the equity market since its trading platform was upgraded to the Genium INET system in November 2015.

The main variables of interest in this study are the option-based order imbalance measures. The time-stamped call and put options data contains information about all transactions, including the initiator of the trade, trade price, contract type (call or put), volume of trade (number of contracts and trade value), settlement price, premium value, strike price and time to maturity. The Turkish derivatives market is entirely order driven with a continuous trading session from its opening in the morning till its close in the evening (session hours change throughout the sample period). The BIST-30 index options are European options that can only be exercised at expiry and are settled in cash. The underlying security is 1/1000 of the BIST-30 index value, and the contract size for the index options is 100 underlying securities. These options expire in the three consecutive expiration months following the month of trade. The expiration months are February, April, June, August, October and December. If December is not one of the three consecutive months after the trading day, it is also included as the fourth expiry date.

An advantage of our data is that it explicitly provides information about the active and passive side of the trade, enabling the identification of the trade initiator.[4] Accordingly, we follow Chordia, Kurov, Muravyev and Subrahmanyam (2021) and compute the call (put) order imbalance as the weekly difference between buyer- and seller-initiated trading volume divided by the total weekly call (put) options volume. The option trading volumes are based on the total number of contracts aggregated in weekly intervals across moneyness and time to maturity. We choose weekly intervals because we expect the daily analysis to be noisy, whereas monthly intervals would substantially reduce the number of observations in the analysis. To understand the links between the options and stock markets, we focus on weekly open-to-close BIST-30 equity index returns as the dependent variable.

The latter part of the study makes use of several other variables. The contingent

[4]Many studies that are interested in the trade initiator information use alternative algorithms (e.g., Lee and Ready (1991)) to classify the direction of the trade. However, this might lead to the wrong classification in more than 15% of the trades (Finucane, 2000; Odders-White, 2000). We do not suffer from this flaw since the granular nature of our data allows the precise identification of buyer- and seller-initiated trades that lead to the exact values of call and put order imbalance.

claims data from Borsa Istanbul contains index options data and BIST-30 index futures tick-by-tick trade information. Like the options data, the futures data also includes the information on the active party that initiates a trade. Therefore, this study computes weekly BIST-30 index futures order imbalance as the difference between buyer-initiated and seller-initiated futures weekly number of contracts divided by the total number of futures contracts traded.

In addition, we compute the aggregate stock order imbalance based on the BIST-30 index components. The transaction data of the individual stocks in the index are also obtained from Borsa Istanbul database. Since the dataset contains the classification of the initiator for each trade belonging to each stock included individually in the BIST-30 index, we aggregate the buyer-initiated and seller-initiated trading volume for each index component weekly. The BIST-30 order imbalance in the spot market is then calculated as the aggregate buyer-initiated number of trades minus the seller-initiated number of trades as a percentage of the total number of trades in the week.[5]

Another variable used in the analysis is the implied volatility of Borsa Istanbul (VBI) derived from BIST-30 index options data. However, since Borsa Istanbul does not have such an official index yet, we construct our own implied volatility index for this market according to the methodology suggested by Sensoy and Omole (2018). In addition, the study makes use of a few macroeconomic indicators. We obtain the Turkish government bond yield data from Bloomberg Database. In particular, one indicator is the one-year Turkish government bond yield, and the other indicator is the term spread computed as the difference between the 10-year bond yield and 1-year bond yield. For the study, we average the daily yields in a week to obtain weekly indicator variables and take the first difference of both variables to obtain the weekly changes.

To compute delta-weighted option order imbalance for each option type (call &

[5] In Borsa Istanbul, index components are updated each quarter. In our analysis, we also update our sample index stocks accordingly.

put), we use Black and Scholes (1973) option pricing model to estimate option delta. Call and put option delta represents option price sensitivity to changes in the underlying stock price and are expressed as $N(d_1)$ and $N(d_1) - 1$, respectively. $N(x)$ is the cumulative probability function for a standardized normal distribution and

$$d_1 = \frac{ln\left(\frac{S_0}{K}\right) + (r + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}$$

where S_0 is the spot index price, K is the strike price, T is the time to maturity in years, σ is the volatility of the spot price and r is the risk-free rate. Each option transaction has a unique option type, time to maturity and strike price. The corresponding index spot price for each options transaction is obtained from BIST-30 intraday index price data. Each day, we use the annualized daily standard deviation of five-minute index returns to compute the underlying index market volatility. Finally, we use the one-year inter-bank lending rates[6] as risk-free return.

3.2.1. Summary statistics

Table 3.1 presents the descriptive statistics and pairwise correlation of weekly order imbalance variables, macroeconomic indicators and option types. Panel A shows the mean, standard deviation, skewness, kurtosis, minimum, median and maximum value of the variables in addition to Jarque-Bera (JB) statistics, Augmented Dickey-Fuller (ADF) and Ljung-Box Q tests. We compute call (put) order imbalance as the weekly difference between buyer- and seller-initiated trading volume divided by the total weekly call (put) options volume. The options trading volumes are based on the total number of contracts aggregated in weekly intervals across moneyness and time to maturity. The mean call order imbalance (Call OIB) and put order imbalance (Put OIB) are -6.36% and -9.97%, respectively. This implies that on average, there is net selling pressure on both call and put options and investors in the options market are more likely to be sellers than buyers in the Turkish option market.

[6]This data is obtained from http://www.trlibor.org

Table 3.1: Descriptive Statistics.

Panel A: Descriptive Statistics

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Min	Median	Max	JB-test	ADF-test	Q-test
Call OIB (%)	-6.357	27.189	-0.146	2.907	-79.093	-5.168	56.815	0.677	-1.120***	0.004
Put OIB (%)	-9.965	27.993	0.080	2.690	-71.128	-9.791	62.240	0.880	-0.925***	0.091
Futures OIB (%)	0.194	3.041	0.551	3.190	-6.915	-0.355	10.499	9.077**	-0.898***	0.065
BIST-30 OIB (%)	0.065	0.036	0.305	2.734	-0.016	0.062	0.170	3.210	-0.779***	0.113
BIST-30 Return (%)	0.115	3.159	-0.859	5.113	-12.212	0.483	7.918	53.78***	-0.955***	0.007
VBI	27.532	5.222	0.629	3.890	17.351	27.518	45.405	17.210***	-0.101***	0.911*
Term Spread (%)	0.011	0.564	-0.579	5.722	-2.170	0.017	1.659	63.070***	-1.044***	0.112
Govt Bond (%)	-0.008	0.681	0.896	13.643	-2.710	0.000	4.039	839.600***	-0.671***	0.381*
Call VOL	2320.069	1795.344	1.675	6.831	120.000	1778.000	11431.000			
Put VOL	2071.259	1852.689	2.522	10.216	139.000	1620.000	10787.000			

Panel B: Pairwise Correlations

	BIST-30 Return	Call OIB	Put OIB	VBI	Futures OIB	BIST-30 OIB	Govt Bond	Term Spread	Call VOL	Put VOL
BIST-30 Return	1.000									
Call OIB	0.201**	1.000								
Put OIB	-0.242**	0.002	1.000							
VBI	0.003	-0.099	-0.026							
Futures OIB	0.649***	0.087	-0.281***	-0.031	1.000					
BIST-30 OIB	0.674***	0.207**	-0.107	-0.045	0.623***	1.000				
Govt Bond	-0.193*	0.000	-0.070	-0.010	-0.013	-0.140	1.000			
Term Spread	-0.182*	-0.060	0.207**	0.009	-0.149	-0.102	-0.515***	1.000		
Call VOL	0.068	0.216**	-0.008	-0.307***	0.006	0.101	-0.067	-0.044	1.000	
Put VOL	-0.120	0.113	0.144	-0.154*	-0.099	-0.057	0.017	0.011	0.757***	1.000

This table presents the descriptive statistics and pairwise correlations of weekly order imbalance measures, macroeconomic indicators and option types. Panel A presents descriptive statistics of the call order imbalance (Call OIB), put order imbalance (Put OIB), futures order imbalance (Futures OIB), stock order imbalance (BIST-30 OIB), weekly spot index returns (BIST-30 Return) and macroeconomic indicators. VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, and Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. Call VOL is the weekly aggregate of the number of call options contracts across moneyness and maturity. Put VOL is the weekly aggregate of the number of put options contracts across moneyness and maturity. The null hypothesis of the Jarque-Bera test is that the variables do not follow a normal distribution. The null hypothesis of the Augmented Dickey-Fuller test is that the variables do not follow a stationary process. The null hypothesis of the Ljung-Box Q-test is that the series is not serial correlated. Panel B shows the pairwise correlations of the variables. The coefficients of all tests are reported with significance levels where *,**, *** represent 10%, 5% and 1% significance levels, respectively. The sample period is between March 2017 and June 2020.

Call option volume is higher than put option volume as the former represents 52.83% of the total option volume, whereas the latter has 47.17% part in total. The average time to maturity of all options in the sample is 41 days. At-the-money options[7] are the most traded option type with 62.78% of the total volume, whereas out-of-the-money options account for 30.34% in total trades and in-the-money options are least traded type of options with a 6.88% share of volume in the market. Furthermore, at-the-money options are the most traded, and in-the-money options are the least traded for both call and put options. The index futures order imbalance (Futures OIB), computed as the difference between buyer-initiated and seller-initiated futures trading volume divided by the total number of futures contracts traded, has a mean value of 0.20%. That is, there is a net buying pressure on index futures on average. Call, put, and futures order imbalance have skewness close to zero, suggesting that the index contingent imbalance measures are approximately symmetric. Weekly spot index return is the natural logarithm of the week's closing price divided by the week's index opening price, capturing the weekly open to close return. The average weekly BIST-30 index return is 0.12%, indicating a slight positive drift in the equity market for the sample period.

Using Jarque-Bera tests, we fail to reject the null hypothesis that call and put order imbalance are not normally distributed. However, the tests suggest that futures order imbalance and all macroeconomic variables depart from normal distributions. ADF tests confirm at 1% significance level that call option, put option and futures order imbalance measures do not contain unit root. In addition, all variables used to control for macroeconomic factors (implied volatility index, government bond yield, term and spread) follow stationary processes. The results of Ljung-Box Q-tests indicate that there is no serial correlation in the weekly open-to-close BIST-30 index returns. Similarly, the index contingent claims, including call

[7]At-the-money options are classified according to the algorithm provided by Bollen and Whaley (2004). In particular, every time index options are traded, we simultaneously check the intraday BIST-30 index value in the spot market with a millisecond precision. If the index option's strike price is higher (lower) than 95% (105%) of the spot index value at that instant, then the traded option is classified as at-the-money.

options, put options and futures contracts order imbalance, are also insignificant. The absence of persistence in the lags reduces the possibility of obtaining dynamic relationships driven by spurious persistence of the order imbalance variables. As a visual representation in order to have a better understanding of the imbalance-return dynamics, we provide Figure 3.1 that displays the order imbalance and weekly index returns.

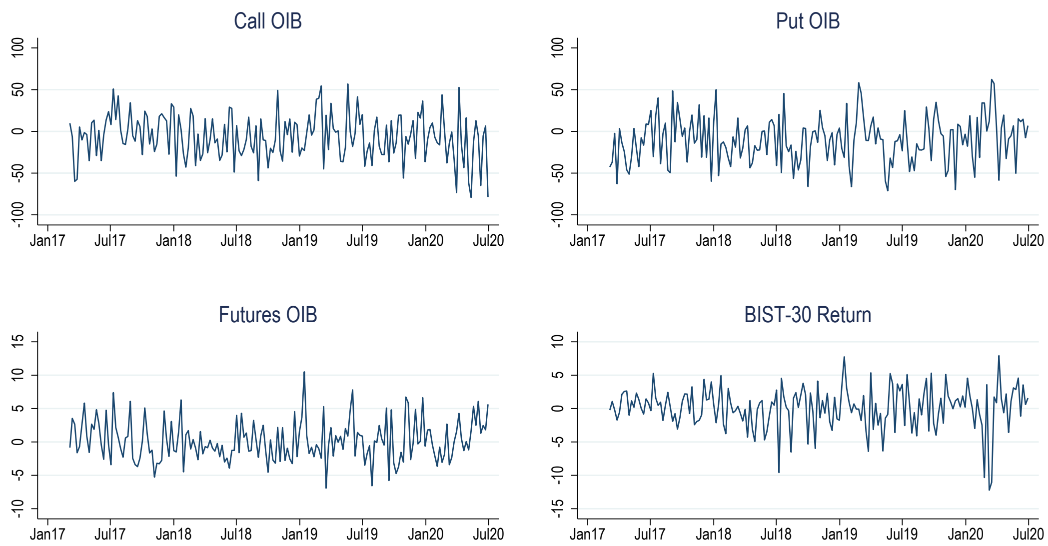

Figure 3.1: This figure displays the weekly order imbalance in index call options, index put options, and index futures, as well as the spot index returns. For all sub-figures, values on the vertical axes are percentage values.

Panel B of Table 3.1 reports the pairwise correlations between weekly index return and the main variables used in this paper. Spot index weekly return is positively correlated with call order imbalance and negatively correlated with put order imbalance. The correlation indicates the contemporaneous relationship between the option imbalance measures and weekly returns. The correlation table shows a low correlation between call option order imbalance and put option order imbalance, implying that they capture different aspects of information in the options market. In addition, there is no correlation between the index returns and total options volume, call option volume and put option volume. It is apparent that correlation with index returns lies in the directional measures but not total volume. Call order imbalance is significantly correlated with the market-wide order imbalance of BIST-30 index components, indicating that buy pressure on the BIST-30 component stocks contemporaneously affects the index price movements in a positive direction. The weekly index return is positively correlated with the futures order imbalance and the market-wide order imbalance of its component stocks.

3.3. Benchmark Results

This section of the paper examines the link between index options trading activity and underlying spot returns. The results establish a contemporaneous relationship between option (call and put) order imbalance and spot returns and demonstrate the predictable reversal effect of call order imbalance on index returns.

3.3.1. Contemporaneous effects

First, we investigate the effect of unsigned options volume and options order imbalance on Turkish spot index return. Table 3.2 displays the results of the regression of weekly index returns on unsigned total option volume, contemporaneous and lagged order imbalance variables. In the first column of Table 3.2, we use total options trading volume as an independent variable and find an economically and statistically insignificant relationship with the index returns. Intuitively, total options volume contains little information about the underlying index returns because the total volume does not differentiate between the trade initiator or the direction of the trade. In other words, the total volume could either be because of the dominance of buyer-initiated transactions, seller-initiated transactions or an even distribution of both. The options market also contains a wide range of possibilities where investors can trade on their information, including positive trade strategies (buy call & write put) and negative trade strategies (write call & buy put), both of which have different implications for the underlying index. Therefore, unsigned option volume conceals the information about the intention of trades in a market.

Table 3.2: Ordinary Least Square Regressions.

VARIABLES	(1) BIST-30 Return	(2) BIST-30 Return	(3) BIST-30 Return	(4) BIST-30 Return	(5) BIST-30 Return	(6) BIST-30 Return	(7) BIST-30 Return	(8) BIST-30 Return
Option VOL	-0.000							-0.000
	(0.706)							(0.467)
Call OIB_t		0.023***	0.027***					0.024***
		(0.008)	(0.002)					(0.005)
Call OIB_{t-1}			-0.019**	-0.019**				
			(0.029)	(0.038)				
Call OIB_{t-2}			0.015*	0.012				
			(0.092)	(0.172)				
Call OIB_{t-3}			-0.017*	-0.014				
			(0.058)	(0.124)				
Put OIB_t					-0.027***	-0.026***		-0.027***
					(0.001)	(0.003)		(0.001)
Put OIB_{t-1}						0.001	-0.001	
						(0.906)	(0.884)	
Put OIB_{t-2}						0.003	0.003	
						(0.752)	(0.744)	
Put OIB_{t-3}						-0.008	-0.012	
						(0.333)	(0.183)	
Constant	0.232	0.263	0.152	-0.009	-0.154	-0.190	0.010	0.224
	(0.554)	(0.278)	(0.557)	(0.973)	(0.534)	(0.504)	(0.971)	(0.579)
Observations	174	174	171	171	174	171	171	174
Adjusted R^2	-0.005	0.034	0.075	0.028	0.052	0.041	-0.007	0.084

This table presents the regression of weekly index returns on unsigned total options volume, contemporaneous and lagged order imbalance variables. Independent variables in the regressions include total option volume (Option VOL), contemporaneous and lagged call order imbalance (Call OIB), contemporaneous and lagged put order imbalance (Put OIB). The regression coefficients are reported with significance levels where *,**, *** represent 10%, 5% and 1% significance levels, respectively. The p-values are reported in parentheses. The sample period is between March 2017 and June 2020.

Separating the trades into transaction-type groups provides richer content in extracting information on the relationship between the index options market and the underlying index. The regression of index returns on contemporaneous call order imbalance indicates that call order imbalance has a significant positive relationship with index returns. That is, an increase in call order imbalance is contemporaneously related to higher index prices. Specifically, we find in column 2 of Table 3.2 that a one standard deviation increase in call order imbalance represents a 0.63% (0.0232×27.189) increase in the weekly open-to-close index returns. According to the information-based view, option trades of investors with positive news lead to an increase in long call trading volume relative to short call trading volume, i.e. higher call order imbalance. As the information becomes reflected in the stock market, there is an increase in underlying asset prices. The hedging-based view holds the same direction prediction at the contemporaneous stage. As call order imbalance increases because of the trades initiated by active investors, counterparties simultaneously hedge their short call option exposure by going long in the underlying equities market, instigating an increase in spot index prices. In addition, we find a contemporaneous negative effect of put order imbalance on index returns. In particular, a one standard deviation increase in put option order imbalance is associated with 0.76% (0.0271×27.993) decrease in index returns. Recall that we define put option order imbalance as the difference between the buyer-initiated number of put contracts and seller-initiated number of put contracts. Therefore, the result shows that buying pressure on put options is associated with a lower return on the underlying asset, as manifested in the weekly spot index return. At the contemporaneous stage, this relationship also aligns with both information and hedging-based views. Buying pressure on put options leads liquidity providers to update their beliefs by reducing prices in the underlying market, causing negative returns. Likewise, the hedging-based view suggests that when there is higher buying pressure on put options, counterparties who are net sellers of put options as a result, hedge their exposure by selling the underlying assets, facilitating lower index returns. In Column 8 of Table 3.2, we add total options trading volume to call and put order imbalance as an additional explanatory variable. We find that the significance level of order imbalances and total options volume remain the same. This result means that call option and put option order imbalance contain information about index price movements in excess of unsigned option volume. This result is consistent with Easley, O'Hara and Srinivas (1998) who find that total options volume is not significant in explaining underlying asset returns but find significance when the total volume is directional and separated into positive and negative option volume. Altogether, the results above reinforce the idea that options volume may conceal important information in the derivatives market because the trading volume does not provide information about price pressures and the initiator of the trades.

3.3.2. Lagged effects

The next set of tests focus on lagged order imbalance effect on index returns to further understand the link between index options and the underlying index. According to the information-based view, option trades aid price discovery, so the contemporaneous relationship between option order imbalance and spot index return is permanent, and the returns do not reverse. However, if the predictability of option order imbalance results from hedging trades of liquidity providers, the sign of the contemporaneous relationship is transitory and therefore reverses. Column 3 of Table 3.2 demonstrates that lagged call order imbalance has a significant negative effect on index returns while the contemporaneous relationship between call order imbalance and index return is positive. Specifically, a one standard deviation increase in call order imbalance is associated with a contemporaneous 0.73% increase in weekly open-to-close spot index return and a 0.52% reduction in the following week, supporting the hedging-based view. When we remove contemporaneous call order imbalance from the model specification (Column 4 in Table 3.2), one week lagged call order imbalance remains significant while other lags become insignificant. This result implies that call order imbalance predicts one-week ahead index returns, i.e., irrespective of the contemporaneous relationship, the lagged call order imbalance has predictive power on the spot index market. A higher buying pressure or a lower selling pressure on call options lead to lower spot index returns in the following week.

The reversal effect observed in this section is unique to call order imbalance. The significant relationship between put options and index returns is merely contemporary and is not sustained beyond the current week. There is no significant price impact of lagged put order imbalance on index returns. Furthermore, earlier result stating that put order imbalance has a negative contemporaneous effect on index returns remains the same when lagged put order imbalance variables are included as explanatory variables as displayed in Table 3.2. While Schlag and Stoll (2005) find contemporaneous relationship between index option and spot index price movements with neither of call nor put option trading predicting future index returns in the German market, call order imbalance is significantly predictive of index returns in the Turkish market. The results in this section show that the relationship between index call options and the underlying spot index subsists when contemporaneous call imbalance is removed from the model. Focusing on the U.S. market, Chordia, Kurov, Muravyev and Subrahmanyam (2021) find that index put option, but not call option, has predictive power over S&P500 return in the following week. The upcoming sections focus on the impact of call order imbalance on next-week index returns in the Turkish market.

3.3.3. Granger causality tests

In the next stage, we use the vector autoregression (VAR) model to understand the dynamic relationship and interactions between the stock index market and two types of index options, namely, call and put options. It is conceivable that the options market has information about the stock market because of the relatively low transaction costs and higher leveraging power of options strategies (Black, 1975). As discussed earlier, the information-based and hedging-based views present two channels through which options market can predict spot returns. On the contrary, some studies posit that the stock market leads options market (Stephan and Whaley, 1990; Chan, Chung and Fong, 2002). Since the literature presents conflicting findings, we use the Granger causality test to understand the direction of predictive power in option and stock markets. In essence, the vector autoregression model allows us to investigate the predictive power of trade volume in the options market on the market-wide index returns after controlling for the lagged weekly return in the stock market, the lags in other contingent markets and the macroeconomic conditions. This leads to the estimation of the following model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t \tag{3.1}$$

where $y_t = [\text{BIST-30 Return}_t, \text{Call OIB}_t, \text{Put OIB}_t, \text{VBI}_t, \text{Govt Bond}_t, \text{Term Spread}_t]'$, β_0 is a (6×1) vector of constant terms, β_i for all i $\in 1, \ldots, p$ are (6×6) matrices, and ϵ_t are (6×1) vectors of error terms. BIST-30 Return is the weekly spot BIST-30 index return, Call OIB (Put OIB) is the weekly call (put) order imbalance, VBI is the implied volatility index, Govt Bond is the first difference of one-year maturity Turkish government bond yield and Term Spread is the first difference of the term spread between 10-year and 1-year maturity Turkish government bond yields. We include the implied volatility index of the Turkish market (VBI) to control for its effect on index option imbalance alongside two macroeconomic indicators (benchmark bond yield and term spread) in the model specification. In this design, we first use the augmented Dickey-Fuller test to reject the null hypothesis that weekly index returns, call order imbalance, or put order imbalance contain unit root (the p-value is less than 1% in each case). Using a causality test, we can demonstrate the direction of information flow between both markets. The significance of β_i will determine whether the markets have predictive power over another, and the magnitude will suggest the extent. Theoretically, lags are included because of several potential reasons that may lead to serial correlation. We use both the Akaike and Bayesian Information Criteria for empirical reasons to limit the number of lags used in the study. We find that the optimal lag is one in both cases.

Table 3.3 displays the results of the Granger causality tests from the vector autoregression model in equation (3.1). The null hypothesis is that row variables do not Granger-cause the variables in the column with the tests' p-values given in parentheses. The first column shows that we reject the null hypothesis that call order imbalance does not Granger-cause index weekly returns. That is, call order imbalance Granger causes weekly index returns. We fail to reject the null hypothesis for put order imbalance, suggesting that there is no significant causal effect of put order imbalance on next week's index returns. The result highlights that call order imbalance, but not put order imbalance, has a predictive effect on spot index returns. We note that call options are more often traded than put options in the sample of this study. Furthermore, there is no evidence that the macro-indicators, measured by term spread and one-year Turkish government bond yield, affect future index returns and vice-versa. The weekly index return has no predictive power on either call option or put option order imbalance. Altogether, the results in Table 3.3 demonstrate that the main predictive power is from call options to index returns.

Figure 3.2 displays the cumulative impulse response functions of call and put order imbalance to the BIST-30 index returns up to 5 weeks ahead. The functions track the evolution of weekly index return following a one standard deviation shock to the option order imbalance. For robustness, we use the generalized impulse response function that is insensitive to the order of the variables in the VAR model. Figure 3.2 shows that a shock to call order imbalance leads to a significant decrease of -19.23 basis points in the week ahead and a cumulative decrease of -17.95 basis points in the five weeks ahead, confirming the Granger causality test results. On the other hand, there is no significant impact of put order imbalance on index returns. The results suggest that an increase in the volume of long calls or a decrease in call writing volume forecasts a decrease in next-week index returns.

Table 3.3: Primary Table.

Panel A: Granger causality tests

	BIST-30 Return	Call OIB	Put OIB	VBI	Govt Bond	Term Spread
BIST-30 Return		-0.030	-0.167	-0.157***	-0.032*	-0.006
		(0.967)	(0.817)	(0.004)	(0.055)	(0.661)
Call OIB	-0.019**		0.290***	-0.002	0.000	0.002
	(0.040)		(0.000)	(0.689)	(0.902)	(0.281)
Put OIB	-0.001	-0.028		0.003	-0.001	0.001
	(0.949)	(0.716)		(0.606)	(0.743)	(0.417)
VBI	-0.008	-0.833**	-0.151		-0.005	0.004
	(0.862)	(0.035)	(0.697)		(0.616)	(0.632)
Govt Bond	0.642	1.824	-0.548	0.263		-0.264***
	(0.138)	(0.626)	(0.881)	(0.347)		(0.000)
Term Spread	0.792	-0.323	7.525*	0.278	0.088	
	(0.130)	(0.943)	(0.091)	(0.411)	(0.398)	

Panel B: Pairwise correlation of residuals of VAR equations

	BIST-30 Return	Call OIB	Put OIB	VBI	Govt Bond	Term Spread
BIST-30 Return	1.000					
Call OIB	0.2045***	1.000				
	(0.007)					
Put OIB	-0.2246***	0.004	1.000			
	(0.003)	(0.954)				
VBI	-0.0104	0.117	0.062	1.000		
	(0.892)	(0.127)	(0.418)			
Govt Bond	-0.2423***	-0.028	-0.052	-0.028	1.000	
	(0.001)	(0.718)	(0.502)	(0.718)		
Term Spread	-0.1615**	-0.042	0.1830**	-0.016	0.4682*	1.000
	(0.034)	(0.587)	(0.016)	(0.837)	(0.000)	

This table presents Granger causality tests and correlation of residuals based on the vector autoregression model in equation (3.1): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return},\ \text{Call OIB},\ \text{Put OIB}, \text{VBI},\ \text{Govt Bond},\ \text{Term Spread}]'$. Panel A displays the parameter estimates of the vector autoregressions with the p-value of the Granger causality tests in parentheses. The null hypothesis is that row variables do not Granger-cause column variables. Call OIB is the call order imbalance, Put OIB is the put order imbalance, BIST-30 Return is the weekly spot index returns, VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, and Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. Panel B presents the correlation of residuals from the vector autoregression equations. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

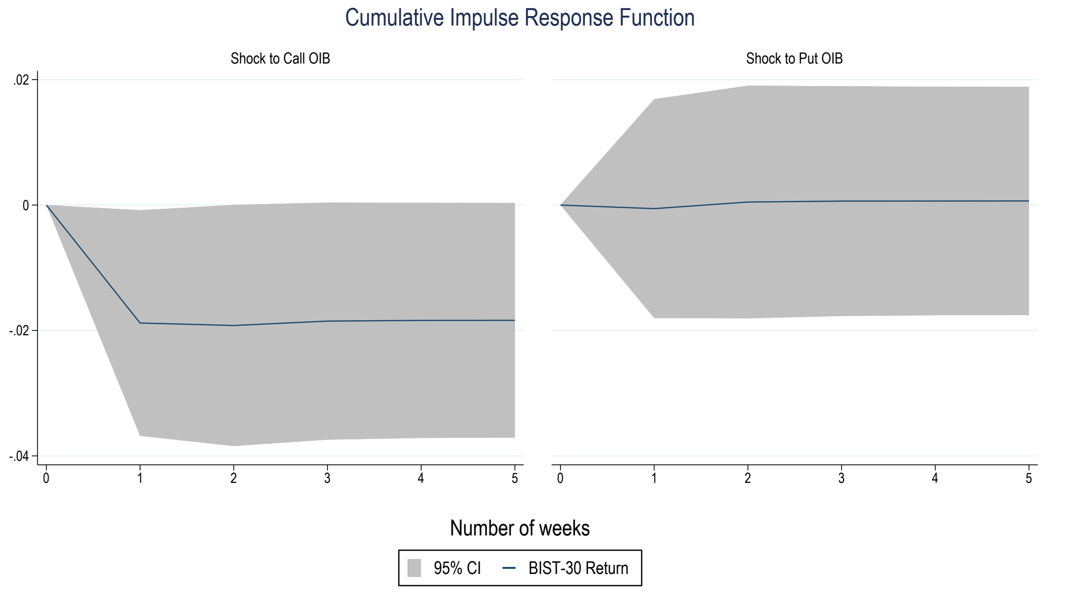

Figure 3.2: Cumulative impulse response functions (with 95% confidence intervals) of call and put order imbalance to the BIST-30 index returns up to 5 weeks ahead.

Generally, the results demonstrate the predictive power of the options market on the spot returns in our sample market.

3.4. Additional Tests

3.4.1. Effect of stock order imbalance and futures order imbalance

Several studies focus on the effect of order imbalance in equity markets, including Chan and Fong (2000), Chordia, Roll and Subrahmanyam (2002), Chordia and Subrahmanyam (2004), and Zhang et al. (2021), find that stock order imbalance predicts stock returns. The need for liquidity providers and market makers to manage risk exposures through quote revisions or hedging strategies in both options and the stock market can impact price dynamics. Hu (2014) highlights that stock order imbalance can predict stock returns either temporarily or permanently. The author claims that the predictive direction of stock order imbalance reverses in the long term if the predictability is driven by price pressure in the stock market, while the predictive direction is permanent if the predictability is a reflection of informed trading. Therefore, the predictive effect revealed in the previous section may be due to the demands specific to equity markets. By controlling for market-wide stock order imbalance in the VAR model, we account for the influence of trades specific to equity markets. Moreover, other studies in the literature find the stock price predictability of option order flow to be insignificant after controlling for stock order flow (Chan, Chung and Fong, 2002; Cao, Chen and Griffin, 2005). In contrast, some others find that stock order flow has no predictive power on index returns (Chordia, Kurov, Muravyev and Subrahmanyam, 2021).[8]

Furthermore, we include index futures because it is an alternative (contingent claim) market for investors to implement trading strategies that reflect their outlook. In addition, hedging demands and informed trades emerging from the futures market can also affect the underlying asset return through the transfer of order imbalance from futures market to stock market (Lee, Ryu and Yang, 2021). The sustenance of the negative predictability of call order imbalance would demonstrate that the options market makes a marginal contribution beyond the information in the futures market in the Turkish market. Schlag and Stoll (2005) find a linkage between index options and the underlying DAX index but reveal that in the German market, index futures rather than index options is the venue for price discovery. Lee, Ryu and Yang (2021) show that option order imbalance loses its predictive effect after controlling for futures order imbalance.

To examine the robustness of the predictive power of call options, we incorporate two additional variables to the VAR model that are likely to have an impact on spot index returns. One variable is the index futures contracts imbalance computed as

[8]For even more robustness, we also wanted to include the order imbalance in BIST-30 ETFs at this stage of our analysis. However, we found out that index ETFs have never gained popularity in Borsa Istanbul, and there was not even a single index ETF that was consistently traded between March 2017 and June 2020. Specifically, during our sample period, we were able to identify three BIST-30 index ETFs, namely IST30, ISY30 and ZPX30. The last one, ZPX30, is a new fund that started trading in March 2020, so it could not be included. On the other hand, the IST30 fund and ISY30 fund stopped trading on January 16th, 2019 and July 8th, 2019 respectively, due to lack of demand. Therefore, order imbalance in index ETFs could not be covered in our empirical investigation.

the difference between weekly buyer-initiated and seller-initiated index futures volume as a percentage of the weekly total index futures volume. The other variable is the weekly market-wide order imbalance (BIST-30 OIB), computed as the difference between aggregate buyer-initiated trading volume and the aggregate seller-initiated trading volume of all the stocks included in the spot BIST-30 index. We estimate the following vector-autoregression model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t, \tag{3.2}$$

$y_t = [\text{BIST-30 Return}_t, \text{Call OIB}_t, \text{Put OIB}_t, \text{Futures OIB}_t, \text{BIST-30 OIB}_t, \text{VBI}_t, \text{Govt Bond}_t,$ $\text{Term Spread}_t]'$, β_0 is a (8×1) vector of constant terms, β_i for all i $\in 1, \ldots, p$ are (8×8) matrices, and ϵ_t are (8×1) vectors of error terms.

Table 3.4 Panel A shows that the Granger causality from call order imbalance to stock index returns remains significant. Predictability of option order imbalance can be a consequence of informed options trading or delta hedging activities of counterparties. The former leads to permanent price changes while the latter leads to temporary price changes through the reversals that occur as the price pressure in the stock market subsides. The result reinforces the hedging-based view. Moreover, Panel B of Table 3.4 reveals that a positive shock to call order imbalance is significantly (correlation = 0.2224, p-value = 0.0034) correlated with positive shock to spot index order imbalance.[9] Here, we highlight the correlation of the residuals rather than the correlation of the original series because it focuses on the impact of exogenous shocks since residuals represent the shock/surprise to the equation in the VAR model. It shows how much influence shocks to the system have on each other. For example, the residual of the VAR equation in which weekly spot index return is the dependent variable represent the part of the index return that is not explained by lagged index return, lagged call option, put option, futures and stock order imbalance and other macroeconomic indicators. Likewise, the residual in the VAR equation where call order imbalance is the dependent

[9]There is an insignificant negative correlation between shock to put order imbalance and stock order imbalance shock, suggesting that buying pressure in put options is not associated with pressure in the spot market.

Table 3.4: Base model plus futures.

Panel A: Granger causality tests								
	BIST-30 Return	Call OIB	Put OIB	Futures OIB	BIST-30 OIB	VBI	Govt Bond	Term Spread
BIST-30 Return		0.353	-0.921	-0.081	0.026	-0.195**	-0.010	-0.013
		(0.730)	(0.362)	(0.482)	(0.845)	(0.011)	(0.672)	(0.522)
Call OIB	-0.019**		0.281***	-0.008	-0.017	-0.003	0.000	0.001
	(0.039)		(0.000)	(0.346)	(0.117)	(0.666)	(0.994)	(0.353)
Put OIB	0.001	-0.048		-0.002	0.011	0.003	-0.001	0.001
	(0.950)	(0.539)		(0.812)	(0.306)	(0.559)	(0.674)	(0.472)
Futures OIB	0.090	-1.222	0.433		0.143	0.038	-0.017	-0.004
	(0.420)	(0.208)	(0.650)		(0.263)	(0.602)	(0.449)	(0.820)
BIST-30 OIB	0.040	0.519	0.643	-0.049		0.020	-0.016	0.013
	(0.684)	(0.542)	(0.443)	(0.605)		(0.759)	(0.425)	(0.455)
VBI	-0.006	-0.848**	-0.132	-0.011	-0.025		-0.005	0.004
	(0.903)	(0.031)	(0.733)	(0.808)	(0.635)		(0.570)	(0.621)
Govt Bond	0.589	2.599	-0.769	0.271	0.481	0.241		-0.261***
	(0.177)	(0.491)	(0.836)	(0.521)	(0.331)	(0.394)		(0.001)
Term Spread	0.751	0.082	7.259	0.263	0.952	0.260	0.097	
	(0.151)	(0.986)	(0.103)	(0.603)	(0.109)	(0.443)	(0.350)	

Panel B: Pairwise correlation of residuals of VAR equations								
	BIST-30 Return	Call OIB	Put OIB	Futures OIB	BIST-30 OIB	VBI	Govt Bond	Term Spread
BIST-30 Return	1.000							
Call OIB	0.2113***	1.000						
	(0.0054)							
Put OIB	-0.2323***	0.0067	1.000					
	(0.0022)	(0.9309)						
Futures OIB	0.6462***	0.0941	-0.2759***	1.000				
	(0.000)	(0.2193)	(0.0002)					
BIST-30 OIB	0.6673***	0.2224***	-0.1156	0.6305***	1.000			
	(0.000)	(0.0034)	(0.1311)	(0.000)				
VBI	-0.0151	0.1207	0.0581	-0.0593	-0.0276	1.000		
	(0.8445)	(0.1147)	(0.4488)	(0.4399)	(0.7196)			
Govt Bond	-0.2362***	-0.0323	-0.0436	-0.0443	-0.1336*	-0.0224	1.000	
	(0.0018)	(0.6740)	(0.5699)	(0.5641)	(0.0807)	(0.7709)		
Term Spread	-0.1642**	-0.0445	0.1805**	-0.1278	-0.1059	-0.0173	-0.4678***	1.000
	(0.0313)	(0.5621)	(0.0178)	(0.0948)	(0.1667)	(0.8215)	(0.0000)	

This table presents Granger causality tests and correlation of residuals based on the vector autoregression model in equation (3.2): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return, Call OIB, Put OIB, Futures OIB, BIST-30 OIB, VBI, Govt Bond, Term Spread}]'$. Call OIB is the call order imbalance, Put OIB is the put order imbalance, BIST-30 Return is the weekly spot index returns, Futures OIB is the futures order imbalance, BIST-30 OIB is the market-wide order imbalance, VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, and Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. Panel A displays the parameter estimates of the VAR equation with the p-value of the Granger causality tests in parentheses. The null hypothesis is that row variables do not Granger-cause the column variables. Panel B presents the correlation of residuals from the vector autoregression equations. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

variable represents the part of the call order imbalance that is not explained by lagged call option, put option, futures and stock order imbalance, lagged spot index return and other macroeconomic variables. The correlation coefficients of residuals reveal the relationship between surprise/shock to the system. The significant contemporaneous correlation between call order imbalance shocks and stock order imbalance shocks is consistent with the hedging-based view that intense call buying pressure significantly impacts stock order imbalance, hence increased stock buying pressure that leads to changes in spot index price.

We also find that the futures order imbalance has no predictive power on the equity market index returns. This result shows that the call option, not other contingent claims, is the sole predictor of index returns. A possible reason is, compared to index futures with linear payoff structure, options allow more flexibility and provide more incentives for speculations and different investment strategies. This advantage can make options more appealing to investors than the futures market (Ryu, Ryu and Yang, 2021). We do not find that index futures lead index options market, neither does options lead futures market. Instead, we find that holding futures order imbalance constant, call option order imbalance has a predictive impact on next-week index returns. The information contained in call options is neither absorbed by stock order imbalance nor index futures imbalance. Moreover, the insignificance of their coefficients implies that neither stock order imbalance nor futures order imbalance have a price impact on the underlying spot next-week index returns.

3.4.2. Role of delta-weighted order imbalance

As it is the nature of the options market, the spot index market underlies multiple options contracts. Investors choose option contracts based on type (call or put), moneyness (in-the-money, at-the-money or out-of-the-money) and time to maturity. Thus, option delta, the sensitivity of option prices to changes in stock index prices, is by definition a function of each option's unique type, moneyness and time to maturity. We use Black and Scholes (1973) option pricing model framework to compute option delta, which is used to aggregate option trades for call and put options separately. After, we follow the approach of Hu (2014) to compute the cumulative delta-weighted option imbalance for each option type. By doing so, we capture the overall delta exposure of counterparties for each option type and analyze its effect on next-week index returns. Liquidity providers become recipients of active option trades and manage their overall risk exposure by trading the underlying asset. Thus, their net position determines their risk exposure and subsequent hedging strategies. When there is a higher delta-weighted option imbalance, there is tremendous pressure on investors to delta-hedge their option exposure in the underlying market Holowczak, Hu and Wu (2014).

The main results demonstrate that the hedging-based view rather than the information-based view is the driver of the predictive power of call order imbalance on index returns. To supplement the main result, we re-estimate the vector autoregression model using delta-weighted order imbalance to precisely capture the overall hedging demand (i.e. delta exposure) present as a result of option trades. We estimate the following vector-autoregression model:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t, \tag{3.3}$$

$y_t = [\text{BIST-30 Return}_t, \delta_t^{call}, \delta_t^{put}, \text{VBI}_t, \text{Govt Bond}_t, \text{Term Spread}_t]'$, β_0 is a (6×1) vector of constant terms, β_i for all i $\in 1, \ldots, p$ are (6×6) matrices, and ϵ_t are (6×1) vectors of error terms.

Table 3.5 presents the Granger causality tests based on the vector autoregression model that replaces Call OIB_t and Put OIB_t with δ_{call} and δ_{put}, respectively as displayed in Equation 3.2. We find that a higher delta-weighted call order imbalance predicts lower next-week spot index returns. This result shows that the transfer of buying pressure from call option to the stock market (as reflected in stock order imbalance) through the hedging trades of counterparties leads to transitory price pressure that subsides in the following week, hence the predictability of negative spot return.

Table 3.5: Impact of delta-weighted imbalance.

	BIST-30 Return	$\delta_{\text{Call OIB}}$	$\delta_{\text{Put OIB}}$	VBI	Govt Bond	Term Spread
BIST-30 Return	0.054	-0.027	-0.121	-0.185***	-0.027*	-0.010
	(0.504)	(0.845)	(0.582)	(0.000)	(0.086)	(0.460)
$\delta_{\text{Call OIB}}$	-0.110**	0.070	0.045	-0.015	-0.002	-0.001
	(0.014)	(0.365)	(0.716)	(0.602)	(0.808)	(0.908)
$\delta_{\text{Put OIB}}$	-0.050*	-0.004	0.039	0.020	-0.003	0.008*
	(0.071)	(0.938)	(0.609)	(0.259)	(0.634)	(0.080)
VBI	0.010	0.051	0.007	0.925***	-0.005	0.003
	(0.821)	(0.519)	(0.953)	(0.000)	(0.613)	(0.721)
Govt Bond	0.707	1.012	0.587	0.533*	0.396***	-0.285***
	(0.144)	(0.225)	(0.657)	(0.083)	(0.000)	(0.001)
Term Spread	0.993*	0.651	-0.167	0.296	0.075	-0.062
	(0.055)	(0.466)	(0.906)	(0.369)	(0.464)	(0.489)

This table reports the parameter estimates and p-values of Granger causality tests in parentheses based on the vector autoregression model in equation (3.3): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return}, \delta_{\text{Call OIB}}, \delta_{\text{Put OIB}}, \text{ VBI, Govt Bond, Term Spread}]'$. The null hypothesis is that row variables do not Granger-cause column variables. BIST-30 Return is the weekly spot index return. δ_{call} is the delta-weighted call order imbalance, δ_{call} is the delta-weighted put order imbalance. VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

3.4.3. Directional imbalance

This part of the study evaluates the separate impact of positive and negative call and put order imbalance on index returns. We run the main VAR model in equation (3.1) again by separating each option imbalance measure into two separate variables. Specifically, Call $\text{OIB}^+ = max(0, \text{Call OIB})$, Call $\text{OIB}^- = min(0, \text{Call OIB})$, Put $\text{OIB}^+ = max(0, \text{Put OIB})$, Put $\text{OIB}^- = min(0, \text{Put OIB})$.

Table 3.6: Directional Imbalance.

	BIST-30 Return	Call OIB+	Call OIB-	Put OIB+	Put OIB-	VBI	Govt Bond	Term Spread
BIST-30 Return		0.038	-0.068	-0.419	0.247	-0.145***	-0.032*	-0.007
		(0.916)	(0.888)	(0.209)	(0.631)	(0.007)	(0.058)	(0.658)
Call OIB^+	0.005		0.096	0.248***	0.209	-0.019	-0.001	0.004
	(0.814)		(0.426)	(0.003)	(0.102)	(0.155)	(0.745)	(0.290)
Call OIB^-	-0.036**	-0.015		0.010	0.151	0.005	0.001	0.000
	(0.019)	(0.814)		(0.864)	(0.109)	(0.612)	(0.852)	(0.986)
Put OIB^+	0.010	0.101	0.003		0.011	0.031**	-0.001	0.003
	(0.635)	(0.250)	(0.982)		(0.931)	(0.019)	(0.840)	(0.424)
Put OIB^-	-0.007	-0.002	-0.103	-0.031		-0.013	0.000	0.000
	(0.618)	(0.973)	(0.194)	(0.567)		(0.148)	(0.882)	(0.908)
VBI	-0.017	-0.036	-0.868***	-0.131	-0.094		-0.004	0.003
	0.705	0.853	0.001	0.467	0.736		0.652	0.723
Govt Bond	0.631	1.793	-0.079	-1.243	0.586	0.245		-0.266***
	(0.142)	(0.322)	(0.975)	(0.463)	(0.822)	(0.372)		(0.000)
Term Spread	0.751	1.404	-1.949	1.627	5.645*	0.332	0.090	
	(0.150)	(0.523)	(0.515)	(0.428)	(0.075)	(0.319)	(0.388)	

This table presents the parameter estimates and the p-value of the Granger causality tests in parentheses based on the vector autoregression model in equation (3.1) with call and put order imbalance segregated into two components: $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return, Call OIB, Put OIB, VBI, Govt Bond, Term Spread}]'$. Call order imbalance (Call OIB) is segregated into positive (Call $\text{OIB}^+ = max(0, \text{Call OIB})$) and negative (Call $\text{OIB}^- = min(0, \text{Call OIB})$) components. Put order imbalance (Put OIB) is segregated into positive (Put $\text{OIB}^+ = max(0, \text{Put OIB})$) and negative (Put $\text{OIB}^- = min(0, \text{Put OIB})$) components. VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, and Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. The BIST-30 Return is the weekly spot index return. The null hypothesis is that row variables do not Granger-cause column variables. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

Table 3.6 presents the Granger causality test results based on the new VAR model. The null hypothesis is that the column variable does not Granger cause the row variable. Accordingly, positive call order imbalance does not have a significant causal relationship with index returns, while negative call order imbalance Granger causes lower index returns. This result implies that the predictive power of call order imbalance documented in earlier results is mainly driven by negative call order imbalance. Since negative call order imbalance implies that the call writing volume is greater than the call buying volume, our finding indicates that BIST-30 index returns increase in the week following high lagged call selling pressure.

This is consistent with the view that price pressures that result from hedging trades strategies by liquidity providers drive the causal effect of call order imbalance on the spot index returns. Call selling pressure is exacerbated when investors in the options market have a negative outlook of the underlying asset value. The counterparty (liquidity provider or market maker) absorbs these trades by hedging their long call option exposure in the underlying spot market with a short position in the underlying, thereby generating lower contemporaneous weekly open-to-close index returns. This is followed by a reversal in spot index price (positive next-week return) towards the fundamental level as the price pressure reduces.

3.4.4. Effect of GDP announcements

To further understand whether the information-based or hedging-based view holds in our sample market, we consider weeks of macroeconomic announcements. While informed investors can use individual equity options to trade on their informational advantage on individual stocks, market-wide index options are more suitable for investors trading on public information about macro-events. According to Ryu, Ryu and Yang (2021), informed investors using index options rely on their sophistication and pace to trade on newly released macroeconomic information. To evaluate the nature of the predictive power of options trading on index returns around macro announcements, we interact call and put order imbalance with positive and negative GDP announcement surprise indicators in the base VAR model, and Table 3.7 displays the result of this specification. GDP announcement is classified as a positive (negative) surprise if the actual GDP announced by the central bank is higher (lower) than the investor consensus before the announcement as obtained from the Bloomberg database.

According to Table 3.7, the call order imbalance is negative and significant while the interaction term GDP $\times$ Call OIB is positive and insignificant for weeks of

Table 3.7: GDP Interaction.

	BIST-30 Return	BIST-30 Return
Call OIB	-0.023**(0.016)	-0.019**(0.033)
Put OIB	-0.001 (0.880)	0.003 (0.776)
VBI	-0.017 (0.711)	-0.017 (0.711)
GDP	1.014 (0.446)	1.963 (0.383)
GDP $\times$ Call OIB	0.072 (0.112)	0.066 (0.318)
GDP $\times$ Put OIB	-0.005 (0.913)	-0.036 (0.518)
Govt Bond	0.620 (0.150)	0.667 (0.117)
Term Spread	0.759 (0.145)	0.888 (0.086)

This table reports the parameter estimates and p-value of Granger causality tests in parentheses based on the vector autoregression model in equation (3.1) with signed GDP announcement dummy variable and its interactions as additional variables. We only display the result of the equation with spot BIST-30 index returns as the dependent variable to save space. Call OIB is the call order imbalance. Put OIB is the put order imbalance. VBI is the Turkish implied volatility index. Govt Bond is the first difference of the one-year Turkish government bond yield. Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bonds. In Column 1 (Column 2), GDP is the indicator variable that equals 1 in weeks of positive (negative) Gross Domestic Product announcement surprise and 0 otherwise. GDP $\times$ Call OIB and GDP $\times$ Put OIB are the interaction of GDP announcement indicator with call and put order imbalance, respectively. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

positive and negative GDP news announcements. This result implies that the hedging-based view dominates the information-based view even in weeks of substantial macro-related information. When we try similar analysis using other public macro-announcements such as inflation, monetary policy rate or unemployment rate announcements, similar results hold as we do not get any significant results on the interactions.[10]

3.4.5. Marginal effects of order imbalance

This section examines the predictive effect of changes in option order imbalance on next-week index returns. We define ΔCall OIB and ΔPut OIB as the first difference of call option and put option order imbalance, respectively. An increase in call (put) order imbalance implies that there is higher call (put) buy pressure in the options market. According to the information-based view, there will be persistence in the direction of the relationship between innovations to option order imbalance and spot returns. However, reversal of direction supports the hedging-based view that an increase in option buy pressure leads to a transfer of temporary price pressure to the spot market. We run the following vector-autoregression model to examine the nature of predictability present in our sample market:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t \tag{3.4}$$

where $y_t = [\text{BIST-30 Return}_t, \Delta\text{Call OIB}_t, \Delta\text{Put OIB}_t, \text{VBI}_t, \text{Govt Bond}_t, \text{Term Spread}_t]'$, β_0 is a (6×1) vector of constant terms, β_i for all i $\in 1, \ldots, p$ are (6×6) matrices, and ϵ_t are (6×1) vectors of error terms.

The results as displayed in Table 3.8 indicate that increase in call option order imbalance predicts negative next-week spot index return at 1% significance level, consistent with earlier results. Shocks to call order buying pressure is reflected in the underlying stock market. In weeks of increased demand pressure on options, liquidity providers increase their hedging demands in the stock market, further

[10]Results for the other macro-announcements are not reported in the manuscript; however, they are available upon request.

Table 3.8: Impact of option innovation.

	BIST-30 Return	Δ Call OIB	Δ Put OIB	VBI	Govt Bond	Term Spread
BIST-30 Return		-0.763	0.769	-0.175***	-0.037	-0.006
		(0.405)	(0.387)	(0.001)	(0.029)	(0.685)
ΔCall OIB	-0.017**		0.176**	0.003	0.001	0.000
	(0.011)		(0.011)	(0.456)	(0.399)	(0.923)
ΔPut OIB	-0.002	-0.147**		0.001	-0.001	0.000
	(0.716)	(0.035)		(0.791)	(0.603)	(0.802)
VBI	0.004	-0.233	-0.339		-0.005	0.003
	(0.922)	(0.637)	(0.479)		(0.603)	(0.744)
Govt Bond	0.670	1.247	-1.080	0.243		-0.264***
	(0.120)	(0.791)	(0.813)	(0.384)		(0.000)
Term Spread	0.782	-0.411	1.184	0.301	0.086	
	(0.129)	(0.942)	(0.829)	(0.369)	(0.405)	

This table reports the parameter estimates and p-values of Granger causality tests in parentheses based on the vector autoregression model in equation (3.4): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return}, \Delta\text{Call OIB}, \Delta\text{Put OIB}, \text{ VBI}, \text{ Govt Bond}, \text{ Term Spread}]'$. The null hypothesis is that row variables do not Granger-cause column variables. The weekly spot BIST-30 index return is the natural logarithm of the week's closing price divided by the week's index opening price. Δ Call OIB is the first difference of call order imbalance. Δ Put OIB is the first difference of put order imbalance. VBI is the Turkish implied volatility index, Govt Bond is the first difference of the one-year Turkish government bond yield, Term Spread is the first difference of the yield differential between 10-year and 1-year Turkish government bond. *,**, *** represent statistical significance at 10%, 5% and 1% levels, respectively. The p-values are reported in parentheses.

driving the relationship.

3.5. Conclusion

We investigate the linkages between the index options market and the underlying benchmark index for one of the most popular emerging markets. The analysis, which covers the period between March 2017 and June 2020, shows that trading in the options market significantly affects contemporaneous and future weekly spot index returns. In particular, an increase in buying pressure relative to selling pressure on call options leads to higher contemporaneous weekly open-to-close index returns with a significant reversal causal effect in the following week. The information-based view predicts that order imbalance leads to a permanent effect on price movements. However, the results in this chapter are consistent with the hedging-based view, which predicts that the direction of the predictability of index option returns by option trades is temporary because the stock market price pressure induced by hedging trades subsides, causing return reversals. This result is consistent with the view of Avellaneda and Lipkin (2003), Ni, Pearson and Poteshman (2005), and Hu (2014) who argue that the options market contains information about the stock market through investor hedging activities. Moreover, re-estimating the vector autoregression model using delta-weighted order imbalance, which captures the cumulative hedging demand of counterparties, leads to the same result.

We find that the predictive power of call order imbalance is sustained after controlling for the order imbalance in both equity and the index futures market, showing that the predictability of spot market by option market trades is neither absorbed by demands specific to the spot market nor the informed or hedging trades that originate from futures market. Segregating call order imbalance into positive and negative components further reveals that the predictive power of call order imbalance is mainly driven by call writing pressure.

The results of this study have implications for future research. First, various studies have shown that different investor types (retail, institutional, foreign, domestic, Etc.) use different information sets when they trade. Identification of investor types would allow the tracking of trades of different investors, thereby providing more clarity on the role of each investor type in the relationship between order imbalance in index option and the spot market. Therefore, when the data is available, studies should examine the subject at the investor type level (e.g., Kuo, Chung and Chang (2015); Bae and Dixon (2018)). Second, this study, together with the works of Schlag and Stoll (2005) on German DAX index, Kang and Park (2008) on Korean KOSPI200 index and Chordia, Kurov, Muravyev and Subrahmanyam (2021) on S&P 500 hint that the predictive ability of index derivatives on the spot index depends on market structure.

Further studies on markets with different structures can provide more empirical information about the linkages between index options and the underlying spot index. Third, in recent years, various exchanges have introduced so-called 'data analytics' as a product to present vital information about their market conditions where some of these analytics include the order imbalance. However, these imbalance related analytics are mostly present for the equity market (e.g., Borsa Istanbul[11]) or the futures market (e.g., Deutsche Borse[12]). Our study reveals that order imbalance in the index options has predictive power on the future underlying index movements. Therefore, introducing real-time analytics for the options market might contribute to price discovery and market efficiency in the spot market.

[11] `https://www.borsaistanbul.com/en/sayfa/2726/equity-market-data-analytics`

[12] `https://www.mds.deutsche-boerse.com/mds-en/data-services/analytics/eurex-real-time-analytics`

CHAPTER 4

ORDER IMBALANCE AND COMMONALITY: EVIDENCE FROM THE OPTIONS MARKET

4.1. Introduction

Traditional models and empirical works in the microstructure literature focus on trading activity as a single security phenomenon. In recent market microstructure literature, the subject of commonality has received significant attention. Commonality refers to the co-variation and spillover effect between individual firm-level trading activities and the entire market over time. In particular, it refers to the sensitivity of individual asset trading activity to corresponding market-wide variations. The bulk of finance research focused on the subject of commonality in order imbalance and liquidity follow the seminal works by Chordia et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001).

Following these studies, numerous papers examine the presence of commonality for different trading activities in different markets[1]. To date, a gap exists in the literature because of the absence of studies on commonality in order imbalance in the derivatives market. Motivated by this, we contribute to the literature by examining and documenting the cross-security presence of common factors in order

[1]Recent papers that explore commonality research include Anagnostidis and Fontaine (2020), Benzennou et al. (2020), Klein and Song (2021), Saad and Samet (2020), and Sensoy (2019).

imbalance in a purely order-driven and emerging derivatives market, namely, the Borsa Istanbul (BIST).

Option markets offer investors an alternative to equities, bonds, and futures markets because of their unique features that make them suitable for informed trading, speculation, and hedging. Furthermore, Cetin et al. (2006) point out that the number of option transactions and the direction of the trades play a significant role in the liquidity and order imbalance structure of the market. The important aspect of this fact is that liquidity and order imbalance in option markets both have price impacts on option prices and thereupon the underlying asset prices. In fact, order imbalance (i.e., the number of buyer-initiated trades minus the number of seller-initiated trades), which either reflects the arrival of new information in the market or can be induced by hedging demand, significantly affects option prices and the associated implied volatility (Bollen and Whaley, 2004). Hu (2014) finds that, through informed or hedging trades by investors in the option market, option order imbalance induces temporary or permanent pressure on underlying stock market price changes. Therefore, the presence of commonality in the single-stock option market, which signifies that order imbalance covaries among options, is relevant to trading decisions by market participants, as it offers new channels for them to consider. Moreover, the presence of systemic variation in option buying/selling pressure with market-wide influence is relevant to policy makers interested in better risk management. Among the earlier studies, Cao and Wei (2010) investigate the commonality in option liquidity, whereas we take a different approach by examining commonality in option order imbalance, which is our main contribution to the literature.

The seminal paper by Chordia et al. (2000) and research by Hasbrouck and Seppi (2001) represent a shift in focus from individual assets to common effects in trading activities, including liquidity and order imbalance. Following these papers, the literature focuses on revealing the drivers of the common components while investigating the presence of commonality in liquidity in different markets, including equities, bonds (Chordia et al., 2005), derivatives (Cao and Wei, 2010), commodities (Marshall et al., 2013), and foreign exchange (Mancini et al., 2013) markets. Chordia et al. (2000), who focus on stocks listed on the New York Stock Exchange, highlight the industry-wide and market-wide factors that affect liquidity, rather than investigating liquidity focused on a single asset. They find a positive relationship between changes in individual asset liquidity and changes in market liquidity, a result that remains robust after controlling for price, volume, and volatility. The commonality in liquidity phenomenon in the equities market showed that liquidity cannot be treated in isolation. Mancini et al. (2013) extend the commonality research to foreign exchange markets, reporting that the level of commonality is higher than is reported in the equities market. They use both the market method and the principal component method to find support for the theory that a reduction in the funding liquidity of investors is followed by market-wide illiquidity in foreign exchange assets.

Most studies have used datasets from quote-driven markets, but some papers focus on order-driven markets. In quote-driven markets, market makers are the liquidity providers of last resort, whereas order-driven markets are free of assigned dealers with market participants' buy and sell orders determining the asset prices. Syamala et al. (2014) document the existence of commonality in liquidity in India's order-driven equity market. Investigating the Turkish market, Sensoy (2017) explores the effect of ownership structure and firm size on the commonality in liquidity and finds that institutional ownership has a positive effect on commonality in liquidity for midcap and large- cap firms whereas the commonality in liquidity in small-cap firms is driven by individual investors. The main result of the research is that higher participation in a firm culminates in heterogeneous investor beliefs, which reflects less commonality in liquidity. In the options market, Cao and Wei (2010) use several option-based liquidity measures between 1996 and 2014 and show commonality in liquidity in the call and put options and that the size and volatility of the underlying asset have an effect on commonality. Verousis et al. (2016) find that the implied volatility of a market index has a strong effect on the market-wide liquidity component. Benzennou et al. (2020) focus on the global financial crisis period between January 2008 and December 2010 and find a commonality in liquidity in the European futures and options market with evidence of a higher level of commonality in derivatives written on same underlying asset.

Focusing mainly on commonality in order imbalance, Hasbrouck and Seppi (2001) use principal component analysis (PCA) and document the existence of comovement in the order flow of 30 stocks in the US Dow Jones Industrial Average (DJIA). Hughen and McDonald (2006) also focus on order flows, segmenting investors (retail and institutional) by trade size (large, medium size, and small), and find commonality across the trades of retail investors, suggesting that sentiment could be the driver of commonality in the equities market. Harford and Kaul (2005) conjecture that indexing is the primary driver of common effects in order flow and returns, unlike in investor allocation and correlation in industry events. That is, firms listed on the S&P 500 have stronger commonality than unlisted firms. Corwin and Lipson (2011) show that program trading by institutional investors, rather than individual investor trades, is the driver of commonality in order flow. Although the issue of commonality in liquidity in options market has been examined in the literature, to the best of our knowledge, no papers to date have investigated the presence of comovement in the options market order flow, in particular, order imbalance.

In our study, using time-stamped transaction-level data, we calculate the daily order imbalance as the difference between the number of buyer-initiated trades and the number of seller-initiated trades for call and put options in the single-stock options market. To investigate the presence of commonality in options order imbalance, we use a market-model methodology based on Chordia et al. (2000) and the PCA of Hasbrouck and Seppi (2001). The market-model method is based on the comovement between individual options order imbalance and the market portfolio that exempts the option in question whereas the PCA method uses the common factors extracted from individual order imbalance as a proxy for a systemic factor. Based on our research, PCA shows that the first principal component explains 7.78 percent of the variations in the call option order imbalance and 11.33 percent of the variations in the put option order imbalance. Further, we find that first principal component explains 27.20 percent of the variations in equity returns. The extracted common effects in the order imbalance are used in time-series regressions to investigate the relationship between individual options order imbalance and market-wide order imbalance commonality in the equity market. Our analysis indicates the presence of positive and statistically significant market-wide common effects in the order imbalance of both call and put options, with a more dominant presence in put options. Specifically, 40 percent and 80 percent of the market-wide call and put options have positive and significant coefficients, respectively. We establish that, after time variation in order imbalance, expiry date effect, and market downturn are controlled for, the documented commonality withstands several robustness checks.

We then analyze the impact of individual and common effects in the underlying equity market on the commonality in the option order imbalance and find no significant relationship. Despite the presence of commonality in the order imbalance in the options market and the equity market, we find no evidence of a significant relationship between individual options order imbalance and market-wide equity order imbalance.

Lastly, we use sequential regressions to examine the contribution of options order imbalance to variations in the underlying equity returns and find that the equity order imbalance makes the highest contribution to stock return variations.

This study makes several contributions to the literature. This is the first study to examine the presence of commonality in order imbalance in the options market. A major implication of this study is that investors need to be aware of the level of commonality in options order imbalance when making their trades because an option's order pressure depends on the buy vs. sell pressure of other listed options. Furthermore, this dependence is higher in put options than call options. Previous papers on commonality in order imbalance focus on quote-driven markets. We examine whether commonality exists in an order-driven market without designated market makers[2]. The attribution of the presence of commonality in order imbalance in financial markets to inventory adjustments and costs in the prior literature may be less pronounced in fully order-driven markets because of the absence of a liquidity provider of last resort, and no market maker is obliged to submit orders. Therefore, it is not immediately clear whether the commonality in order imbalance documented in developed markets holds in emerging markets with a different market structure. Thus, we extend the commonality literature by investigating the presence of common effects in an order-driven emerging option market. The result that options order imbalance has minor effects on underlying asset returns provides insight into one of the potential reasons for the slow growth of a derivatives market in emerging markets. Our results can be generalized to other emerging markets (e.g., China, India, Brazil, Russia, Korea) with a fully order-driven derivatives market and a similar market structure.

The rest of the paper proceeds as follows. Section 4.2 discusses the data. Section 4.3 describes the methodology. Section 4.4 presents the results, and Section 4.5 concludes.

4.2. Data

The Turkish derivatives market at the Istanbul Stock Exchange became operational in December 2012. The futures and options exchanges (Turkish Derivatives Exchange and Borsa Istanbul Derivatives Market) merged in August 2013 under the umbrella of the BIST, which became the only exchange in Turkey. Several

[2]See https://www.borsaistanbul.com/en/sayfa/2284/market-making/. Although many derivatives products have market makers, single equity options do not, nor does the equity market.

types of derivatives contracts are traded, including single stock options and futures, equity index options and futures, and commodity and currency futures. Although relatively new compared to other emerging markets, the BIST derivatives market exchange ranked thirteenth by the number of trades, and the BIST single-stock futures and options ranks second globally among the most actively traded, with over one billion trades in 2020,[3] making the securities trading on the BIST among the most active in the world.[4]

The Turkish option market is a fully order-driven market with no designated market makers. All the listed options are European options and expire on the last trading day of the month. There are six maturity months: February, April, June, August, October, and December. At any point in time, option contracts with an expiration in the next three expiry months are traded. If December is not one of these expiry months, a fourth contract with expiration in December is added. Each option has a contract size of 100 shares of its underlying equity, and the tick size is 0.01 points per share. Our sample begins on March 1, 2017, because it is the day that Nasdaq's Genium INET trading system was developed and adopted for the Turkish derivatives market under the name BISTECH with facilities such as collocation and ITCH and OUCH terminals, which allow trading at very high speeds. The characteristics of the BIST option market makes it interesting for studying the presence of common effects among single-stock options. The results of this study can serve as a benchmark for comparing the results obtained from an emerging market with those found for developed markets and other emerging markets. In particular, emerging markets with a similar market size and structure can benefit from our findings.

We obtain time-stamped high-frequency transaction-level option and equity data from the BIST database between March 1, 2017, and February 28, 2021. The

[3] In fact, the Borsa Istanbul has the world's highest trading in single-stock futures and precious metals futures. See https://www.world-exchanges.org/our-work/articles/derivatives-report-2020/.

[4] For more details, see also https://www.fia.org.

database contains time-stamped data on the option type, maturity date, number of transactions (buyer or seller initiated), and trading volume of all exchange-traded options. The option market has 21 unique firms in 7 different sectors: Akbank, Garanti Bank, Halk Bank, Is Bank, Sabanci Holding, Vakif Bank, and YapiKredi in financial; Aselsan, Koc Holding, Pegasus, Sisecam, Turkish Airlines in manufacturing; Eregli, Kardemir, and Petkim petroleum in raw materials; Arcelik and Tofas in consumer goods; Turkcell and Turk Telekom in communications; Tupras in energy; and Emlak Konut in real estate. We exclude Aselsan from the study because it has many missing days of transaction data, making it impossible to calculate the principal components of its option. Because organized option trading was introduced in 2013, none of the 21 single-stock options listed at inception has been removed from the exchange, and no further additions have been made. We further exclude deep in-the-money and deep out-of-the-money contracts from our sample.[5] We exclude these options because they are thinly traded (deep-in-the-money and deep-out-of-the-money options represent 3.01 percent of all option transactions) and to avoid issues related to the pricing structure. We keep options with a maturity date of between 8 and 365 days. Industry and other firm-specific data are obtained from the Bloomberg database. For the part of the analysis that involves investigating the link of commonality in the options and equities markets, we obtain transaction-level data on the underlying equity market from the BIST. All aspects of our data analysis are based on the time period 9:00 am to 5:30 pm.

We use the transaction-level data to construct daily order imbalance measures. All trades occur within the organized exchange, with precise information about trade initiators. Therefore, we have explicit information about whether the buyer or seller is the active side of the trade, allowing us to calculate the call (put) order imbalance as the daily number of buyer-initiated call (put) trades minus the

[5] Because every transaction is time stamped to the millisecond, we match each option transaction with the underlying stock price and calculate moneyness as a strike price divided by a stock price. An option is classified as deep-out-of-the-money if the moneyness is greater than 1.20 for calls or less than 0.80 for puts and classified as deep-in-the-money if the moneyness is less than 0.80 for calls or greater than 1.20 for puts.

number of seller-initiated call (put) trades. Similarly, the equity order imbalance is calculated as the difference between the total number of daily buyer-initiated equity trades and seller-initiated equity trades.[6] That is, whether it is a derivative or an equity, order imbalance is defined as:

$$\text{OI} = \text{Number of buyer-initiated trades} - \text{Number of seller-initiated trades} \quad (4.1)$$

Following the literature, we define all order imbalance measures in terms of the number of transactions, rather than the trading volume, and standardize order imbalance measures to make the order imbalance comparable across firms. Specifically, the standardized order imbalance measure is given by

$$\text{OI}^*_{i,t} = \frac{\text{OI}_{i,t} - \mu_i}{\sigma_i} \quad (4.2)$$

where μ_i, and σ_i are the firm-specific mean and standard deviation over the sample period. Before standardizing the variables, we perform tests to confirm the stationarity of each firm's call (put) order imbalance. Table 4.1 reports the augmented Dickey-Fuller test statistics and corresponding significance levels. For each single-stock option in our sample, we reject the null hypothesis that the series contains a unit root at the 1 percent significance level, confirming that the variables are stationary. We calculate the daily open-to-close stock returns as the natural logarithm of the difference between the daily opening and closing prices of the underlying asset. That is, $R_{i,t} = \ln(p_{c,it}/p_{o,it})$, where $R_{i,t}$ is the daily return, and $p_{o,it}$ and $p_{c,it}$ are the opening and closing prices on day t for firm i, respectively.

Table 4.1 summarizes the transaction characteristics of firms with individual equity options listed on the BIST. We report the time-series mean of the daily call order imbalance, put order imbalance, the number of trades of put and call options, the underlying equity return, and the market capitalization of firms with listed options.

[6] Because our sample market is fully order driven, all limit and market orders are revealed in the order book. All orders in system are continuously matched at the best buy and sell prices.

Table 4.1: Summary Statistics.

Ticker	Company Name	Call OI	Put OI	Call Trades	Put Trades	Return (%)	Market Cap	ADF Test^{Call}	ADF Test^{Put}
AKBNK	Akbank	195.47	141.18	1044.05	1754.11	-0.01	34403.38	-8.54***	-9.06***
ARCLK	Arcelik	12.10	15.93	154.17	356.06	0.07	13630.96	-8.36***	-8.87***
EKGYO	Emlak Konut	198.56	51.19	3672.90	2857.22	-0.01	7557.97	-9.49***	-9.27***
EREGL	Eregli Demir	-16.79	63.00	284.43	483.63	0.11	31628.66	-9.16***	-8.33***
GARAN	Garanti Bank	30.34	208.59	565.43	1517.41	0.03	38183.71	-9.97***	-8.88***
HALKB	Halk Bank	52.42	286.63	766.08	1419.74	-0.05	10839.11	-11.28***	-6.96***
ISCTR	Is Bank	-9.83	132.48	761.65	1279.61	0.01	27513.16	-8.34***	-9.44***
KCHOL	Koc Holding	0.69	62.59	338.43	751.46	0.05	42798.58	-8.14***	-8.75***
KRDMD	Kardemir	88.37	-4.00	2352.51	3155.40	0.21	3372.18	-10.42***	-8.20***
PETKM	Petkim	111.35	15.26	1630.71	2307.53	0.04	8920.33	-8.85***	-10.00***
PGSUS	Pegasus	-3.04	20.86	149.24	274.67	0.23	4122.84	-10.36***	-9.72***
SAHOL	Sabanci Holding	4.03	62.87	231.01	889.03	0.02	18942.84	-9.96***	-9.63***
SISEE	Sise ve Cam	2.42	128.21	1482.35	1461.91	0.08	12295.00	-8.19***	-9.04***
TCELL	Turkcell	75.85	209.10	667.92	1173.37	0.05	29809.80	-8.81***	-8.46***
THYAO	Turkish Airlines	187.81	286.99	1061.81	1758.71	0.12	17490.84	-9.22***	-8.04***
TOASO	Tofas Turk	-0.47	4.10	62.19	219.61	0.05	12529.26	-9.49***	-8.73***
TTKOM	Turk Telekom	4.51	120.70	257.53	1113.89	0.06	21481.11	-9.61***	-7.05***
TUPRS	Tupras Petrol	11.91	28.04	105.92	206.69	0.04	27881.26	-9.45***	-7.81***
VAKBN	Vakif Bankasi	36.67	46.73	861.36	1921.44	0.00	14041.86	-10.21***	-7.37***
YKBNK	Yapi ve Kredi Bankasi	77.04	132.95	2862.43	2514.93	0.00	19091.72	-10.74***	-8.08***
Cross-sectional Mean		52.97	100.67	1060.01	1498.87	0.06	19826.73		

This table displays the time-series mean of the properties of equity options listed on Borsa Istanbul and the average across stocks over the period March 2017 to February 2021. The last two columns describe the daily return and market capitalization of the stocks. Call (Put) OI denote call (put) order imbalance, defined as the difference between the number of buyer-initiated call (put) and seller-initiated call (put) trades. Call (Put) Trades are the daily average of the total number of call (put) option trades. Return is the daily logarithmic open-to-close return of the underlying stock in percentage. Market Cap is the average market capitalization of underlying assets over the sample period. ADF Test means the augmented Dickey-Fuller test statistics for call and put order imbalance series. *, **, and *** significant at 10%, 5%, and 1%, respectively.

The sample data cover 1,000 trading days. The mean number of call option trades is 1,060.01, and the mean number of put option trades is 1,498.87. This shows that individual put options are traded more often than call options. Positive mean call and put option order imbalances indicate that active investors are net buyers of individual call and put options on average.[7] The average market capitalization of firms with listed options over the sample period is TL 19,826.73 million, and their average daily open-to-close stock return is 0.06 percent.

4.3. Methodology

This section presents the approach used to investigate the presence of commonality in order imbalance in the Turkish derivatives market.[8] To do this, we use a market-model method based on Chordia et al. (2000) and the principal component method based on Hasbrouck and Seppi (2001). The market-model method depends on the cross-sectional average of order imbalance variables to extract common factors, and the principal component method relies on the variance-covariance matrix of the variables. We then examine the impact of trading activity in the underlying equity market on the equity option order imbalance. Finally, we describe the approach that investigates the relationship between individual and market-wide option order imbalance and underlying asset returns.

4.3.1. Commonality in Option Order Imbalance: Market-Model Approach

Chordia et al. (2000) use a market-model method to detect the presence of commonality in liquidity in the US market. Several papers have extended the market-model method to investigate the presence of common factors in order imbalance in the equity market, such as Harford and Kaul (2005) in the S&P 500 and Bailey

[7]Although the summary statistics report the raw numbers, firm-level order imbalance measures are standardized throughout the study to eliminate the potential distortion effect.

[8]Various aspects of the BIST have been the subject of academic studies in recent years (Buyukkara et al., 2021; Ocak et al., 2021; Sahin and Kuz, 2021; Tinic et al., 2020). However, order imbalance is a subject that has not been considered before.

et al. (2009) in the Shanghai Stock Exchange. To document commonality in option order imbalance, the market model time-series regression that we use is given by:

$$\mathrm{OI}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{M,t} + \beta_{2,i}\mathrm{OI}_{M,t-1} + \beta_{3,i}\mathrm{OI}_{M,t+1} + \gamma X + \epsilon_{i,t} \tag{4.3}$$

where i denotes individual firms, $\mathrm{OI}_{i,t}$ is the daily option (call or put) order imbalance, $\mathrm{OI}_{M,t}$ ($\mathrm{OI}_{M,t-1}$ and $\mathrm{OI}_{M,t+1}$) are the contemporaneous (lagged and lead) market-wide option order imbalance, and X represents the control variables. This approach produces firm-by-firm regressions of option order imbalance (call and put separately) on the market-wide option order imbalance and other control variables. The market-wide order imbalance is the cross-sectional average of all individual option order imbalance, excluding the ith firm. We exclude firm i to reduce the cross-sectional dependence of the coefficients of the market-wide order imbalance. The year dummy variable, which equals 1 in the year of trading and 0 otherwise, captures the yearly changes in option order imbalance. The rollover of option positions to the next contract on the date of expiry can lead to commonality across listed options, thus we include an expiry date variable to take this into account. The expiry day variable equals 1 on the last business day of each expiry month, and 0 otherwise. For each firm, we standardize all variables with the time-series mean and standard deviation to enable comparison. The significance of the coefficient of market-wide option order imbalance indicates the relationship between individual option and market-wide option order imbalance and the cross-sectional mean of the time-series regression provides the level of commonality present in the Turkish derivatives market. We calculate the t-statistics across stocks and take the average of the adjusted R^2.

4.3.2. Commonality in Option Order Imbalance: Principal Component Approach

In addition to the market-model approach, we also use PCA to examine the presence of comovement in order imbalance. The principal component approach, following Hasbrouck and Seppi (2001), extracts common factors by constructing order imbalance factors as a linear combination of firm-level order imbalance variables. The method captures the common variation in order imbalance measures across firms, allowing the derivation of a smaller set of variables that can explain the original order imbalance variables for each type of option.

For each $i = 1, 2, ..., 20$, let X_i be a vector of length T such that $X_i = [x_{i1}x_{i2}...x_{iT}]^{'}$. x_{it} is the standardized order imbalance of firm i at time t. Let Σ be the covariance matrix of $X = [X_1, X_2, ..., X_{20}]$. Given that

$$\Lambda_j = \lambda_j X = \lambda_{1j}X_1 + \lambda_{2j}X_2 + ... + \lambda_{20j}X_{20} \tag{4.4}$$

is a linear combination of the order imbalance variables from each firm, the variance of Λ_j, $\mathrm{Var}(\Lambda_j) = \lambda_j^{'}\Sigma\lambda_j^{'}$. The first principal component is the component that maximizes $\mathrm{Var}(\Lambda_j)$ subject to the constraint that $\lambda_1^{'}\lambda_1 = 1$. The second principal component is the linear combination that maximizes $\mathrm{Var}(\Lambda_j)$ subject to the constraint that $\lambda_2^{'}\lambda_2 = 1$ and is uncorrelated with the first principal component. Thus, the method allows the calculation of 20 principal factors with each factor mutually uncorrelated. The ith eigenvector, λ_i, of the covariance matrix is the weight of the variables in the linear combination that forms the ith principal component. Because the order imbalance variables are standardized, the proportion of the total variation that is explained by the ith principal component is given by $p_i = \frac{\lambda_i}{n}$. Eigenvalues are not significantly different from 1 if the variables have no common factors.

We then use the extracted first principal component to proxy for market-wide order imbalance in time-series regressions discussed in Equation 4.3. That is, the regression is given by:

$$\mathrm{OI}_{i,t} = \alpha_i + \beta_{1,t}\mathrm{P}_{M,t} + \beta_{2,t}\mathrm{P}_{M,t-1} + \beta_{3,t}\mathrm{P}_{M,t+1} + \gamma X + \epsilon_{i,t} \tag{4.5}$$

where $\mathrm{P}_{M,t}$ is the first principal component that proxies for market-wide option order imbalance and X represents the control variables as described in Section 4.3.1.

4.3.3. Impact of Trading Activity in the Underlying Asset

This section examines the impact of trading activity in the underlying equity market on commonality in order imbalance. We use the following firm-by-firm time-series regression:

$$\mathrm{OI}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{M,t} + \beta_{2,i}\mathrm{OI}^{\mathrm{Equity}}_{i,t} + \beta_{3,i}\mathrm{OI}^{\mathrm{Equity}}_{M,t} + \epsilon_{i,t} \tag{4.6}$$

where $\mathrm{OI}_{M,t}$ is the market-wide option order imbalance, $\mathrm{OI}^{\mathrm{Equity}}_{i,t}$ is the individual equity order imbalance, and $\mathrm{OI}^{\mathrm{Equity}}_{M,t}$ is the market-wide equity order imbalance. In the market-model method, market-wide equity order imbalance is calculated as the cross-sectional equally weighted average of the underlying equity order imbalance, excluding firm i. In the principal component method, we extract the first principal component of equity order imbalance and add it as an independent variable to proxy for market-wide equity order imbalance. A significant $\beta_{2,i}$ would demonstrate that equity order imbalance has a contemporaneous effect on option order imbalance, and a significant $\beta_{3,i}$ would suggest that option order imbalance is associated with the equity order imbalance inherent to other firms with exchange-listed options. Continuous significance of $\beta_{1,i}$ shows that the commonality in option order imbalance dominates individual or common effects that arise from the underlying assets. In some instances, order pressure can spill over from the equity market to the option market and vice-versa.

4.3.4. Relationship between Commonality in Equity and Option Order Imbalance and Underlying Asset Returns

We examine the impact of individual and market-wide equity order imbalance and individual and market-wide option order imbalance in explaining variations in the underlying equity returns. We also examine and compare the influence of equity and equity option order imbalance on the underlying returns using sequential regressions (Corwin and Lipson, 2011; Hasbrouck and Seppi, 2001). We begin with the estimation of individual equity order imbalance impact on the underlying stock returns, followed by the market-wide equity order imbalance, then add individual option order imbalance, and finally the market-wide option order imbalance. The estimation of firm-by-firm time-series regressions (for call and put separately) is given by:

$$\mathrm{R}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{i,t}^{\text{Equity}} + \beta_{2,i}\mathrm{OI}_{M,t}^{\text{Equity}} + \beta_{3,i}\mathrm{OI}_{i,t} + \beta_{4,i}\mathrm{OI}_{M,t} + \epsilon_{i,t} \tag{4.7}$$

where $\mathrm{R}_{i,t}$ is the daily open-to-close stock return of stock i on day t, $\mathrm{OI}_{i,t}^{\text{Equity}}$ is the corresponding equity order imbalance, $\mathrm{OI}_{M,t}^{\text{Equity}}$ is the market-wide equity order imbalance, $\mathrm{OI}_{i,t}$ is the individual option order imbalance, and $\mathrm{OI}_{M,t}$ is the market-wide option order imbalance. In the market-model method, market-wide equity (option) order imbalance is calculated as the cross-sectional equally weighted average of equity (option) order imbalance, excluding the firm i. For the principal component method, we extract the first principal component of the equity order imbalance and add it as an independent variable to proxy for market-wide equity order imbalance. The study reports the incremental and cumulative R^2 of each model.

4.4. Results

This section presents the results of our analysis on the presence of commonality in option order imbalance in the Turkish market, followed by an investigation of the link between the equity and option markets.

4.4.1. Commonality in Option Order Imbalance: Market-Model Approach

Hasbrouck and Seppi (2001), Harford and Kaul (2005), and Bailey et al. (2009) provide evidence of common factors in the order imbalance in equity markets. This section examines the presence of commonality in option order imbalance using the market-model method of Chordia et al. (2000). Table 4.2 presents the results of market-wide order imbalance commonality in the option market, showing clear evidence of this commonality in both call and put options. Among the firms with exchange-listed call options, 75 percent have positive coefficient on

Table 4.2: Commonality in order imbalance regressions.

	Market Model		Principal Component Analysis	
	Call	Put	Call	Put
Concurrent market-wide order imbalance	0.181***	0.487***	0.111***	0.199***
T-statistics	(3.632)	(7.699)	(2.485)	(8.523)
% Positive	75	100	65	100
% Positive significant	40	80	50	90
Lagged market-wide order imbalance	-0.012	0.074**	-0.003	-0.001
T-statistics	(-0.270)	(2.000)	(-0.308)	(-0.066)
% Positive	40	65	65	45
% Positive significant	15	20	10	40
Lead market-wide order imbalance	-0.014	0.074*	0.000	-0.003
T-statistics	(-0.633)	(1.742)	(-0.007)	(-0.375)
% Positive	50	70	55	40
% Positive significant	0	25	0	15
Adjusted R^2 Mean	0.005	0.040	0.079	0.115
Adjusted R^2 Median	0.004	0.023	0.019	0.085

This table summarizes the time-series regressions of individual option (call and put) order imbalance on contemporaneous, lagged, and lead market-wide option order imbalance: $\mathrm{OI}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{M,t} + \beta_{2,i}\mathrm{OI}_{M,t-1} + \beta_{3,i}\mathrm{OI}_{M,t+1} + \gamma X + \epsilon_{i,t}$. The table reports the cross-sectional average of coefficients from time-series regressions with t-statistics in parentheses, percentage of positive coefficients, percentage of positive coefficients significant at the 5% level, and the cross-sectional mean and median adjusted R^2 of time-series regressions. *, **, and *** significant at 10%, 5%, and 1%, respectively. The market-model method calculates market-wide order imbalance as the cross-sectional equally weighted average of order imbalances, excluding firm i, and the principal component method uses the extracted first principal component as the market-wide option order imbalance. All order imbalance variables are standardized using cross-sectional mean and standard deviation. The sample covers 1,000 trading days from March 2017 to February 2021.

market-wide call option order imbalance, and 40 percent of the coefficients of market-wide call option order imbalance are positive and significant. The results indicate that the cross-sectional average of the beta coefficient of market-wide call option order imbalance is 0.181, and it is statistically significant at the 1 percent level (t = 3.632). The results display an even stronger level of commonality in put options, in which all firms have positive coefficients on market-wide put option order imbalance, and 80 percent of them are positive and significant. The average of the beta coefficients of individual put option order imbalance is 0.487, with a t-statistic of 7.699 (significant at 1 percent level). Further investigation shows that the commonality demonstrated is significantly greater in put options than in call options. Specifically, we find that the mean difference between the coefficients of market-wide call and put order imbalance is significant at the 1 percent level. We note that the cross-sectional average of the adjusted R^2 for call and put options are 0.5 percent and 4.0 percent, respectively. Although this appears modest, it is comparable to the average adjusted R^2 of less than 2 percent reported in Chordia et al. (2000). The stronger comovement of the put options than the call options signals that the investors use put options for hedging purposes more widely than call options. One reason for this is the order types used in the Turkish financial markets. On the BIST, different markets have different order types. One of the order types available to investors in the derivatives market is "stop orders," which is activated when the market price reaches a predetermined level. This predetermined price should be higher than the market price on the buying side and lower on the selling side. This conditional order type provides a kind of an insurance for investors and is used for hedging purposes against sharp market movements. However, the BIST stock market has no such order type. Therefore, if an investor has a portfolio in the spot market, the only hedging opportunity protecting the investor from sharp price falls is to buy a put option in the derivatives market. This strategy prevents the investors from losing more than the premium paid for the option. In the event of sharp falls in the spot market, it is always extremely hard to sell the stocks at a predetermined price. However, if an investor has a put option, then she can sell the asset at the strike price and stop her losses.

In the BIST option market, for the put option contracts, the sellers are usually institutional investors, and the buyers are individual investors. As explained earlier, the two strategies for preventing losses in the spot market are either to buy a put option or to sell a call option. For individual investors, it is easier and cheaper to buy a put option than to sell a call option. When market figures are considered, it is also obvious that investors prefer to buy put options, rather than trade call options. In fact, Table 4.1 indicates that the average number of put option trades is greater than the average number of call option trades. Specifically, the ratio of the average number of put options trades to call option trades is approximately 3 : 2.

Some market experts also argue that the put option strategies that the individual investors prefer results from the reduction in the number of large and foreign investors who hold large portfolios in the spot market. The share of foreign investors in the spot market dropped from 65.79 percent in January 2020 to 44.32 percent in March 2021. This decline means that a third of the foreign investors had sold their portfolios.

Overall, the results show that buying pressure is correlated among individual options, with a stronger presence documented in the put options market.[9] Moreover, the regressions show that the commonality effect is not driven solely by the option expiry date, the trading year, or a market downturn.[10]

[9] In addition to performing market-wide regressions, we check for the existence of industry-wide commonality in order imbalance in sectors with more than three firms (finance and manufacturing) and obtain similar results.

[10] In unreported regressions, we add interaction terms for an expiry day dummy and market-wide order imbalance as well as interaction terms for market downturn and market-wide order imbalance as independent variable and find no evidence of stronger commonality on option maturity dates.

Table 4.3: Principal components analysis for order imbalance variables.

	Call			Put			Equity		
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Eigenvalue	1.555	1.392	1.334	2.265	1.414	1.378	5.441	1.680	1.357
Proportion	0.078	0.070	0.067	0.113	0.071	0.069	0.272	0.084	0.068
Cumulative	0.078	0.147	0.214	0.113	0.184	0.253	0.272	0.356	0.424

This table displays the results of principal component analysis for call option order imbalance, put option order imbalance, and equity order imbalance. All firm-level order imbalance variables are standardized using cross-sectional mean and standard deviation. For each variable, the table reports the eigenvalues and the proportional and cumulative contribution to total variations explained by the first three principal components.

4.4.2. Commonality in Option Order Imbalance: Principal Component Approach

This section uses PCA to analyze the commonality in option order imbalance. First, we provide PCA results and then report the results of time-series regressions on exchange-listed options. Table 4.3 reports the PCA estimation for order imbalance variables. To facilitate comparison with prior research focused on commonality in order imbalance for the equity market, we report the PCA for firms with exchange-listed options. The first principal component for equity order imbalance has an eigenvalue of 5.441, that is, it explains 27.2 percent of the total variations. The evidence in Corwin and Lipson (2011), which focuses on 100 stocks listed on the NYSE, suggests that first principal component of order imbalance explains 4.9 percent of the total variation whereas the first three principal components explain 7.87 percent of the total variation. The results by Hasbrouck and Seppi (2001), which mainly focus on 30 Dow stocks, indicate that the first principal component in order imbalance explains 7.8 percent of the total variation. Thus, our result implies higher strength in the first principal component in our sample equity market. The eigenvalue of the first principal component for call options is 1.555, which suggests that it explains 7.78 percent of the variations in call option order imbalance, and the first three principal components explain 21.40 percent of the total variation. However, the first principal component for put option order imbalance is 2.265, which indicates that it explains 11.33 percent of the variation, and the first three principal components explain 25.3 percent of the total variation. The results strongly demonstrate the presence of common factors in our sample market. The highest commonality appears strongest in equity order imbalance followed by put options, then call options.

We now address the impact of common factors in option order imbalance on individual option order imbalance for each type of option. Table 4.2 presents the results of the regression in which the first principal component is used as the market-wide factor. The coefficient of market-wide call order imbalance is positive for 65 percent of the firms, with an average of 0.111 (significant at the 1 percent level), and 50 percent of the coefficients are positive and significant. Moreover, the average adjusted R^2 of the regression is 7.9 percent. The mean coefficient of market-wide put order imbalance is 0.199 (significant at 1 percent level), and all coefficients are positive, of which 90 percent are significant. The average adjusted R^2 for this regression is 11.5 percent. These results are consistent with those of the market-model method. That is, put options have stronger commonality than call options. Overall, the explanatory power of the regressions is greater in the principal component method than the market-model method. The earlier results in the literature show that investors use equity option order imbalance to predict individual stock price movement. Focusing on the option market, we find that option market investors learn from the order imbalance of other equity options when making trading decisions. These results provide evidence of an incremental role of equity options in the Turkish market. In other words, beyond using the options market as a venue for trading information about the underlying asset, options markets also use the information contained in order imbalance to trade other equity options. Because the single equity options market has no designated market maker, the results signify that investors in derivatives market learn from the order imbalance in listed derivatives.

4.4.3. Impact of Trading Activity in the Underlying Asset

This section examines the additional effect of individual and market-wide order imbalance in the equity market on individual option order imbalance. Chordia et al. (2005) find a relationship between the commonality of liquidity in the bond and equity markets. They attribute the relationship to the movement of investors across different asset classes. Investors can choose to trade in option and equity markets, based on their expectation after the arrival of new information in the market. For instance, when positive (negative) news arrives in the market, investors can either buy call (put) options or buy (sell) the underlying asset. The presence of simultaneous trading that leads to intense buying or selling pressure in both markets at such moments can lead to a correlation in order imbalance in both equity and option markets. The direction of the common effects is positive when the trades are in the same direction and negative if there is reverse trading in the two markets. Even in the absence of information, the hedging strategies of investors in the two markets can also lead to correlation in order imbalance. Some investors trade options to hedge their equity exposure whereas liquidity providers might use equity market trades to hedge option trades by active investors. For instance, if there is high buying pressure, the passive investors on the other side of the trades can choose to hedge their option exposure in the underlying equity market. Therefore, demand related to hedging needs and information arrivals that link equity and option market lead to the transmission of buying and selling pressure across the markets, potentially leading to correlation in common factors. Thus, we add equity order imbalance to our model specification to understand the influence of order imbalance in the equity market on the order imbalance commonality in the option market.

Table 4.4 reports the results of the regressions. We report the results of the principal component method, which demonstrate higher explanatory power for the variables related to the market-model method. The mean coefficient of market-wide option order imbalance is significantly higher than the coefficient on both

Table 4.4: Impact of trading activity in underlying asset on option order imbalance.

	Market Model						Principal Component					
	Call			Put			Call			Put		
Market-wide option order imbalance	0.178***	0.182***	0.184***	0.518***	0.519***	0.519***	0.111***	0.111***	0.112***	0.198***	0.199***	0.199***
T-statistics	(3.591)	(3.723)	(3.778)	(7.511)	(7.552)	(7.587)	(2.486)	(2.512)	(2.520)	(8.391)	(8.415)	(8.436)
% Positive	75	75	75	100	100	100	65	65	65	100	100	100
% Positive significant	40	40	40	80	80	80	50	50	50	90	90	90
Individual equity order imbalance		-0.002	0.002		-0.006	-0.001		-0.002	0.010		0.000	0.000
T-statistics		(-0.162)	(0.092)		(-0.605)	(-0.097)		(-0.133)	(0.582)		(-0.013)	(0.047)
% Positive			45		45	50		45	60		45	45
% Positive significant			5		5	10		5	5		0	0
Market-wide equity order imbalance			-0.011			-0.020			-0.007			0.000
T-statistics			(-0.531)			(-0.977)			(-1.517)			(0.078)
% Positive			45			35			40			45
% Positive Significant			1			1			5			10
Prop. R^2 (%)	0.485	0.401	0.151	3.554	0.196	0.143	7.775	0.342	0.155	11.326	0.183	0.117
Cumulative R^2 (%)	0.485	0.885	1.037	3.554	3.750	3.894	7.775	8.117	8.272	11.326	11.509	11.626

This table summarizes the time-series regressions of individual option (call and put) order imbalance on market-wide option order imbalance, individual equity order imbalance, and market-wide equity order imbalance: $\mathrm{OI}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{M,t} + \beta_{2,i}\mathrm{OI}^{\mathrm{Equity}}_{i,t} + \beta_{3,i}\mathrm{OI}^{\mathrm{Equity}}_{M,t} + \epsilon_{i,t}$. The table reports the cross-sectional average of coefficients from time-series regressions with t-statistics in parentheses, percentage of positive coefficients, percentage of positive coefficients significant at the 5% level. The table reports the proportional and cumulative R^2 of the regressions where proportional R^2 represents the contributions of each variable to the regressions. *, **, and *** significant at 10%, 5%, and 1%, respectively. The market-model method calculates the market-wide order imbalance as the cross-sectional equally weighted average of order imbalances, excluding firm i, and the principal component method uses the extracted first principal component as the market-wide order imbalance. All order imbalance variables are standardized using cross-sectional mean and standard deviation. The sample covers 1,000 trading days from March 2017 to February 2021.

individual and market-wide equity order imbalance. This shows that buying pressure increases in an individual option when there is higher buying pressure on other options. The results indicate that changes in individual option order imbalance are not driven by trading in the underlying equity market. Other than the regression coefficients, the R^2 of the regressions has similar implications. Common effects explain 7.78 percent of the variations in individual call order imbalance. Equity order imbalance contributes additional explanatory power of 0.34 percent whereas market-wide equity order imbalance adds explanatory power of 0.16 percent to variations in call order imbalance. We find that the first principal component explains 11.36 percent of the variations in put order imbalance. Equity order imbalance contributes explanatory power of 0.18 percent, and market-wide equity order imbalance explains an additional 0.12 percent of the variation in put order imbalance. Overall, the results suggest that an option's buying/selling pressure is influenced by the buying/selling pressure of other options, but buying pressure in the equity market has little influence on changes in option buying pressure. That is, there is a modest transfer of pressure from stock order imbalance to equity options order imbalance in our sample market. Therefore, the main drivers of commonality in order imbalance in the option market are specific to trades on the option market.

4.4.4. Relationship between Commonality in Equity and Option Order Imbalance and the Underlying Asset Returns

So far, this paper has revealed the presence of commonality in call and put option order imbalance in the Turkish market. This section examines the contribution of option order imbalance to explaining equity returns, after accounting for the explanatory power of individual and market-wide order imbalance in the equity market. Hasbrouck and Seppi (2001) document that a common factor in equity order imbalances influences the underlying equity returns, implying that, beyond the impact of trading activity within a stock, the buying pressure on other stocks in the market also affects returns. The results in Section 4.4.2 indicate the strong presence of commonality in equity order imbalance in BIST. Specifically, the market-wide equity order imbalance explains 27.2 percent of the total variations in individual order imbalances. Therefore, we examine the relationship between returns and order imbalance in a multimarket framework using sequential regressions. We add the variables based on our expectation and prior literature that individual stock order imbalance is likely to have an effect on stock returns, followed by other factors.

Table 4.5: Explained stock return variations by stock and option order imbalance.

	Market Model								Principal Component							
	Call				Put				Call				Put			
Individual equity order imbalance	0.012***	0.009***	0.009***	0.009***	0.012***	0.009***	0.009***	0.009***	0.012***	0.008***	0.008***	0.008***	0.012***	0.008***	0.008***	0.008***
T-statistics	(18.069)	(12.221)	(12.163)	(12.157)	(18.069)	(12.221)	(12.162)	(12.195)	(18.069)	(8.842)	(8.827)	(8.827)	(18.069)	(8.842)	(8.807)	(8.817)
Market-wide equity order imbalance		0.014***	0.014***	0.014***		0.014***	0.014***	0.014***		0.003***	0.003***	0.003***		0.003***	0.003***	0.003***
T-statistics		(13.794)	(13.794)	(13.751)		(13.794)	(13.750)	(13.838)		(9.903)	(9.897)	(9.883)		(9.903)	(9.878)	(9.953)
Individual option order imbalance			0.000	0.000			0.000	0.000			0.000	0.000			0.000	0.000
T-statistic			(-0.734)	(-0.681)			(0.681)	(-0.095)			(-0.563)	(-0.532)			(0.640)	(-1.089)
Market-wide option order imbalance				-0.001				0.002***				0.000				0.001***
T-statistic				(-5.383)				(6.063)				(0.728)				(6.929)
Prop. R^2 (%)	27.082	6.782	0.181	0.034	27.082	6.782	0.066	0.110	27.082	6.479	0.181	0.026	27.082	6.479	0.062	0.146
Cumulative R^2 (%)	27.082	33.865	34.046	34.080	27.082	33.865	33.931	34.041	27.082	33.561	33.742	33.768	27.082	33.561	33.623	33.769

This table summarizes the time-series regressions of stock returns on individual and market-wide equity and option order imbalance: $\mathrm{R}_{i,t} = \alpha_i + \beta_{1,i}\mathrm{OI}_{i,t}^{\mathrm{Equity}} + \beta_{2,i}\mathrm{OI}_{M,t}^{\mathrm{Equity}} + \beta_{3,i}\mathrm{OI}_{i,t} + \beta_{4,i}\mathrm{OI}_{M,t} + \epsilon_{i,t}$. We sequentially run regressions of equity returns on individual equity order imbalance and then add market-wide equity, then individual option order imbalance and finally market-wide option order imbalance. We report the cross-sectional average R^2 from firm-by-firm time-series regressions, which represent the proportional and cumulative contributions of each independent variable in explaining return variations. We also report the cross-sectional average of coefficients from time-series regressions with t-statistics in parentheses. *, **, and *** significant at 10%, 5%, and 1%, respectively. Market-wide equity and option order flow are calculated using market-model and principal component methods. Market-model method computes market-wide order imbalance as the cross-sectional equally weighted average of underlying order imbalance, excluding firm i, and the principal component method uses the extracted first principal component as the market-wide option order imbalance. All order imbalance variables are standardized using cross-sectional mean and standard deviation. All R^2 are reported in percentages. The sample covers 1,000 trading days from March 2017 to February 2021.

Table 4.5 reports the cross-sectional averages of the R^2 of firm-by-firm time-series sequential regressions described in Equation4.7 for both the market-model and principal component methods. The results of both methods are comparable; therefore, we report the output of the principal component method. According to the principal component method, individual equity order imbalance explains 27.08 percent of the variations in equity returns, and market-wide equity order imbalance contributes explanatory power of 6.48 percent in the Turkish market. For their part, Hasbrouck and Seppi (2001) find that stock order imbalance explain 25 percent of the changes in returns for 30 Dow stocks whereas Corwin and Lipson (2011) report that individual stock order imbalance explains 8.83 percent of stock return variations for 100 major NYSE stocks. Individual call order imbalance accounts for 0.18 percent of the variations in stock returns whereas market-wide call option order imbalance explains an additional 0.03 percent of the variation in returns. We note that commonality in put order imbalance explains more variation in returns than individual put order imbalance. After accounting for both individual and common effects in order imbalance in the equity market, individual put order imbalance explains 0.06 percent of the variations in equity returns whereas market-wide put order imbalance explains 0.15 percent. Overall, the results show that a significant proportion of changes in the returns on the underlying asset is driven by individual equity order imbalance, followed by the common effect in equity order imbalance. The magnitude of explanation provided by option order imbalance is comparatively minute.

4.5. Conclusion

This study fills a void in the microstructure literature by examining the presence of commonality in order imbalance in the options market. The commonality literature has become popular in recent times following the work of Chordia et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001), which are all focused on NYSE stocks. Subsequently, the literature has been extended to bonds, commodities, and foreign exchange markets; however, research on the option market has remained scarce. Using a dataset on the Turkish option market, which is fully order driven, covering 1,000 trading days between March 2017 and February 2021, we use the popular market-model and principal component approaches and find consistent evidence of common effects in order imbalance in the option market. We find significantly higher commonality in put options order imbalance than in call options. The results hold after factors likely to affect individual option order imbalance, such as yearly variations in order imbalance, the expiry day effect, and overall market downturns, are controlled for. We also explore the effect of individual and market-wide equity order imbalance on the order imbalance in the option market. After accounting for the explanatory power of market-wide option order imbalance, the results show that, for both call and put options, changes in individual option order imbalance are not driven by buying (selling) pressure in the underlying equity market.

We further investigate the contribution of option order imbalance to variations in underlying equity returns. The extant literature has established the price impact of order imbalance in the equity market, and, consistent with earlier literature, we demonstrate that individual equity order imbalance as well as market-wide equity order imbalance explain a substantial portion of variations in the underlying asset returns. However, the results indicate that the additional contribution of individual and market-wide option order imbalance to the explanatory power of stock returns is minimal.

The results on the presence of commonality indicate that shocks to buying/selling pressure in the option market have market-wide effect. An implication of these results is that, in addition to focusing on the underlying asset, it is also important to consider other listed options when creating option trade strategies and forming investment portfolios. Our findings also motivate us to ask whether a similar phenomenon might exist in the single-stock futures market because single-stock options and futures contracts on the BIST are written on the same underlying assets. Finally, the equity market of the BIST has a product called real-time data analytics, which includes order imbalance data for the equity market.[11] Considering the commonality in order imbalance in the derivatives market and its importance on the systemic risks evidenced in our study, it might be a good idea to introduce a similar analytics product for the derivatives market as well for better risk management and a more efficient market.

[11] https://www.borsaistanbul.com/en/sayfa/2727/market-data-products/

To further understand the common effects in option order imbalance, future research can focus on the composition of the types of traders (individual and institutional investors) in the option market to shed light on the drivers of the common effects. This study focuses on the Turkish market, but it is worthwhile to investigate whether the pattern of common effects in option order imbalance exists in other order-driven and quote-driven markets or in other emerging and developing markets.

CHAPTER 5

CONCLUSION

This dissertation explores the impact of transactions in the equity options market on financial market outcomes. We discuss the key results below. In the first main chapter, we estimate the implied volatility index for the Turkish equity market (VBI) and discuss parameter selections and procedures followed in the computation as compatible with the rapidly growing Borsa Istanbul options market. The chapter finds that VBI strongly predicts future realized volatility of the underlying equity index. Furthermore, we find that the forward-looking VBI is a stronger predictor of future volatility than the historical realized volatility. Examining the relationship between VBI and other domestic and global financial indicators discloses that VBI is correlated with foreign exchange rates against Turkish lira, local currency government bond yields, CDS written on the USD dominated Turkish sovereign bonds, MSCI global stock market index and the financial conditions of the eurozone. Although the correlation is not significant when compared with crude oil and gold prices, U.S. treasuries with ten years maturity, financial conditions of U.S., and the implied volatilities of U.S. and selected eurozone equity markets. Overall, the results show that VBI can be an essential tool for effective risk management by investors, policymakers and academics in the Turkish market.

The second chapter investigates the nature of feedback between the Turkish index options market and the underlying benchmark index. We find that trading in the options market has a significant effect on contemporaneous and future weekly spot index returns. An increase in call (put) option order imbalance is associated with higher (lower) contemporaneous weekly open-to-close index returns. The results suggest that there is a significant causal effect of call option order imbalance on underlying index returns in the following week. Consistent with the hedging-based view of Avellaneda and Lipkin (2003), Ni, Pearson and Poteshman (2005), and Hu (2014) who argue that option market contains information about the stock market through investor hedging activities, our results suggest that the direction of the predictability of index option returns by option trades is temporary because the stock market price pressure induced by hedging trades subsides, causing return reversals. The results subsist when we re-estimate the model using delta-weighted order imbalance that captures the cumulative hedging demand of liquidity providers and market makers. We also find that the predictive ability of call order imbalance remains after controlling for the order imbalance in both equity and the index futures market. This suggests that the predictability is not absorbed by any of the information or hedging demands of market participants originating from the futures market. After separating call order imbalance into positive and negative components, we find that call writing pressure drives the main results. The results in the chapter imply that the market structure plays a role in the nature of feedback between index options and equities markets. Moreover, the introduction of real-time order imbalance related analytics products for the index options market might contribute to the price discovery and market efficiency in the spot market.

To the best of our knowledge, the final chapter is the first study in the microstructure literature to examine the presence of commonality in order imbalance in the options market. Focusing on the fully order-driven emerging Turkish individual options market, we use market-model and principal component approaches and find consistent evidence of common effects in individual call and put option order imbalance. The results which hold after considering other factors that are likely to affect individual option order imbalance, such as yearly variations in order imbalance, the expiry day effect, and overall market downturns, show that there is a significantly higher level of commonality present in put options order imbalance than in call options. Further analysis shows that changes in individual option order imbalance are not driven by buying or selling pressure in the underlying equity market for both call and put options. Consistent with the microstructure literature, we find that individual equity order imbalance and market-wide equity order imbalance explain a substantial portion of variations in the underlying asset returns. In addition, the additional contribution of individual and market-wide option order imbalance to the explanatory power of stock returns is minimal. An implication of the results is that shocks to buying/selling pressure in the options market have a market-wide effect. Therefore, it is crucial for market participants to account for order imbalance in other listed options when creating option trade strategies and forming investment portfolios. Similar to one of the implications in the third chapter, the result suggests the introduction of order imbalance analytics products for individual options given the importance of derivatives markets as it relates to systemic risks.

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