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Information content of order imbalance in the index options market☆

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A B S T R A C T

We use proprietary transaction level data of Borsa Istanbul to compute the order imbalance of index options in order 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 spot index return predictability by call options is absorbed neither by the stock order imbalance nor the index futures imbalance. Indeed, this predictability 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 is the driver of predictability. Results are robust after controlling for various factors.

1. Introduction

Finance literature offers several views on the nature of feedback that exists between option 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 option 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 signal from option trades, they update their beliefs by increasing (decreasing) 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 option volume on future stock prices is contained in the trade of informed investors. Under this information-based view, option 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 option on stock market dynamics. Avellaneda and Lipkin (2003) propose a model that demonstrates how delta-hedging can have impact on underlying stock prices, particularly around expiry dates. The model predicts that underlying stock prices converge towards the strike price of options 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

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of market makers contribute to 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. This hedging trades lead to changes in stock order flow causing temporary stock price pressures, thus changes in stock price movements. We exemplify this dynamic with call options. When there is increased call buying pressure in the option market that places the counterparties (market makers and liquidity providers) in a short call position, the counterparties simultaneously delta-hedge the short call option exposure with long position in the underlying market since the options are European call options. The hedging demand is reflected as an increase in demand in the stock market and causes the stock order imbalance to increase, leading to an increase in the price of the underlying. Conversely, if there is a net call selling pressure in the market, the passive investor, the liquidity provider or market maker in the order driven derivatives market, is in long call option position. The counterparties dynamically hedge the option exposure by short selling the underlying index, leading to a decrease in underlying asset price and lower weekly index return.

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

Our main goal 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 particularly focus on the nature of the predictive relation between index options and the underlying index. Turkish option market structure is different from the market structure 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 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 trade. This difference suggests a potentially different informational role for the Turkish index option market.

This study contributes to the literature that investigates the information flow between equity and derivatives market. While some studies find that option market contains information about the dynamics of the stock market, 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 price lead stock prices. Later, Easley et al. (1998) develop a pooling equilibrium model in which investors can trade information in both stock and options market. 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 former leads the latter. On the other hand, Stephan and Whaley (1990) find evidence that stock price movements lead 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 as well as option quotes, but not option net trade volume, contain information about changes in the stock market. Their result suggests that informed investors initiate trades in options market only when the value of information is large. 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 option instruments in forecasting underlying asset movements leaves the predictive power of options market as an empirical question that remains unresolved. We employ vector autoregression model to assess the lead–lag relationship between stock and options market.

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 clearly an important descriptor that allows us to understand the general sentiment and direction the market is headed.[1] For example, using put–call ratio computed as buyer-initiated put option volume divided by total buyer-initiated option volume as a measure of informed trading in options market, Pan and Poteshman (2006) find evidence of informed option 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 in 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 DAX index futures market, rather than 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

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

for the underlying index returns. Li, French, and Chen (2017) demonstrate the presence of informational content in SPX options around 2008 financial crisis, suggesting that investors use market-wide information to generate profit. The information can be due to access to private information, ability to process public information more accurately or different interpretation for same information. Very recently, Luo, Yu, Qin, and Xu (2020) show that single stock option 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 above-mentioned literature 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 et al. (2020), we work at the market-wide index level, not individual equities.

This study finds a contemporaneous positive (negative) effect of call (put) order imbalance on index returns while total option volume has no significant relationship with index returns, supporting the notion that total option volume conceals information about the linkage between option and stock market. Furthermore, we find a negative effect of lagged call order imbalance on index returns. To understand this phenomenon, we examine causality relationships between the Turkish spot index and the associated derivatives using vector autoregression (VAR) model. 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 option market, information trades and hedging demands in the futures market can also lead to the transfer of order imbalance to stock market that can result in changes in spot prices. In addition, buying pressure specific to stock market can have an impact on price dynamics. Therefore, we further 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, call options and not other contingent claims is 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 option 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 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 predictive power of index options on spot returns in weeks of major macroeconomic news announcements. In such weeks, information-based view is likely to hold if informed investors with private information or sophistication to quickly trade newly released public news use the option market to their advantage. However, our results show that hedging-based view continues to dominate for call option 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 option market exposure in the spot market. The result shows that delta-weighted order imbalance has a causal effect on next-week return in the negative direction, 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 paper 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 paper is related to Chordia et al. (2021) who examine the predictability of market returns from index option 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 structure and liquidity. The different levels of liquidity and market structure hint at a different feedback mechanism between options and stock market from the U.S. market which is the main 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. In fact, 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 that there is 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 2 describes the Turkish option market and the data used in this study. Section 3 presents the methodology and provides the main results. Section 4 reports the additional tests. Section 5 concludes.

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 2019 year-end, 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.

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

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

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 fully 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 the 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 et al. (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) option volume. The option trading volumes are based on total number of contracts aggregated in weekly intervals across moneyness and time to maturity. We choose weekly intervals because we expect that daily analysis would be noisy whereas monthly intervals would substantially reduce the number of observations in the analysis. To understand the links between the options market and the stock market, we focus on weekly open-to-close BIST-30 equity index returns as the dependent variable.

The latter part of the paper makes use of several other variables. The contingent claims data from Borsa Istanbul contains not only index options data but also BIST-30 index futures tick-by-tick trade information as well. 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 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 on a weekly basis. The BIST-30 order imbalance in the spot market is then calculated as the aggregate buyer-initiated number of trades minus 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. The Turkish government bond yield data are obtained 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 purpose of 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 & put), we use Black and Scholes (1973) option pricing model to estimate option delta. Call and put option delta represent the sensitivity of option price 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 unique option type, time to maturity and strike price. The corresponding index spot price for each option 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] 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.

[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 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 leads to the exact values of call and put order imbalance.

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

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

Table 1
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 number of call options contracts across moneyness and maturity. Put VOL is the weekly aggregate of number of put options contracts across moneyness and maturity. The null hypothesis of Jarque–Bera test is that the variables do not follow normal distribution. Null hypothesis of Augmented Dickey–Fuller test is that the variables do not follow a stationary process. Null hypothesis of Ljung–Box Q-test is that the series are 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.

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

2.1. Summary statistics

Table 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. Call (put) order imbalance is computed as the weekly difference between buyer- and seller-initiated trading volume divided by the total weekly call (put) option volume. The option trading volumes are based on 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 a 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.

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 small 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, put and futures order imbalance measures do not contain unit root. In addition,

[7] At-the-money options are classified according to the algorithm provided by Bollen and Whaley (2004). In particular, for every time there is an index options 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 the 95% (105%) of the spot index value at that instant, then the traded option is classified as at-the-money.

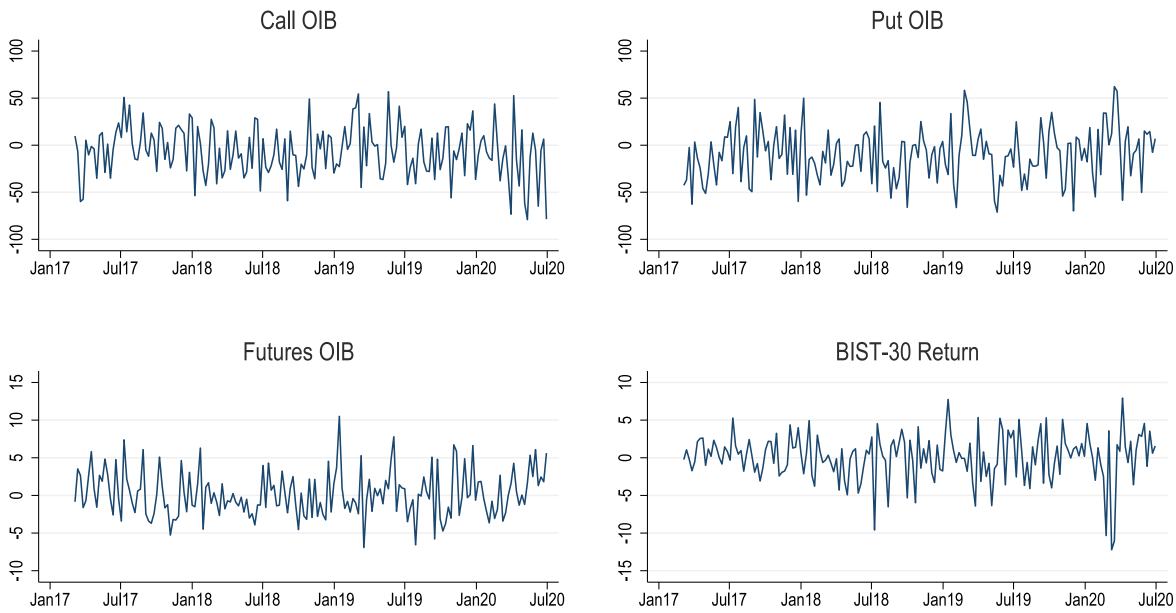

Fig. 1. This figure displays the weekly order imbalance in index call options, index put options, and index futures as well as the spot index returns. For all sub-figures, values on the vertical axes are percentage values.

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 show that there is no serial correlation in the weekly open-to-close BIST-30 index returns. In similar fashion, the index contingent claims including call 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 Fig. 1 that displays the order imbalance and weekly index returns.

Panel B of Table 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. This indicates the contemporaneous relationship between the option imbalance measures and weekly returns. The correlation table shows that there is a low correlation between call order imbalance and put order imbalance, implying that both capture different aspects of information in the options market. In addition, there is no correlation between the index returns and total option 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. Benchmark results

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

3.1. Contemporaneous effects

As a first step, we investigate the effect of unsigned options volume and option order imbalance on Turkish spot index return. Table 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 2, total option trading volume is used as an independent variable and we find an economically and statistically insignificant relationship with the index returns. It is intuitive that total option volume contains little information about the underlying index returns because total does not differentiate between trade initiator or the direction of the trade. In other words, total volume could either be because of the dominance of buyer-initiated transactions, seller-initiated transactions or an even distribution of both. Option market also contains 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 2
This table presents the regression of weekly index returns on unsigned total option 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.

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

Separating the trades into transaction-type groups provides richer content in trying to extract information on the relationship between index options market and the underlying index. A regression of index returns on contemporaneous call order imbalance shows that call order imbalance has a significant positive relationship with index returns. That is, increase in call order imbalance is contemporaneously related to higher index prices. Specifically, we find in column 2 of Table 2 that a one standard deviation increase in call order imbalance represents 0.63% (0.0232 × 27.189) increase in the weekly open-to-close index returns. According to the information-based view, trades of investors with positive news leads 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 order imbalance is associated with 0.76% (0.0271 × 27.993) decrease in index returns. Since put order imbalance is the difference between buyer-initiated number of put contracts and seller-initiated number of put contracts, the result shows that a buy 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 market makers to update their beliefs by reducing prices in the underlying market, causing negative returns. Likewise, 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 2, total option trading volume is added to call and put order imbalance as additional explanatory variable and we find that the significance level of order imbalances and total option volume remains the same. This means that call and put order imbalance contain information about index price movements in excess of unsigned option volume. This result is consistent with Easley et al. (1998) who find that total option 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 option volume may conceal important information in the derivatives market because trading volume does not provide information about price pressures and the initiator of the trades.

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 is as a result of hedging trades of market makers, the sign of the contemporaneous relationship is transitory and therefore reverses. Column 3 of Table 2 demonstrates that even though the contemporaneous relationship between call order imbalance and index return is positive, there is a significant negative effect of lagged call order imbalance on index returns. 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 is followed by 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 2), one week lagged call order imbalance remains significant while other lags become insignificant. This result indicates that call order imbalance predicts one-week ahead index returns, i.e., irrespective of the contemporaneous relationship, the lagged call order imbalance has a predictive power in 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 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 imbalances are included as explanatory variables as displayed in Table 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 et al. (2021) find that index put option, but not call option, has predictive power over S&P500 return in the following week. The upcoming sections place extra focus on the impact of call order imbalance on next-week index returns in the Turkish market.

3.3. Granger causality tests

In the next stage, we use 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 option market has information about stock market because of the relatively low transaction costs and higher leveraging power of option strategies (Black, 1975). As discussed earlier, information-based and hedging-based view present two channels through which option market can predict spot returns. On the contrary, some studies posit that stock market leads options market (Chan et al., 2002; Stephan & Whaley, 1990). 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, 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 stock market, the lags in other contingent markets and the macroeconomic conditions. This leads to the estimation of the following model:

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

where $y_t = \left[\text{BIST-30 Return}_t, \text{Call OIB}_t, \text{Put OIB}_t, \text{VBI}_t, \text{Govt Bond}_t, \text{Term Spread}_t\right]'$, 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 calculated with the methodology by Sensoy and Omole (2018), 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 augmented Dickey–Fuller test to reject the null hypothesis that any of weekly index returns, call order imbalance or put order imbalance contains unit root (the p-value is less than 1% in each case). With the use of 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. For empirical reasons, we use both the Akaike and Bayesian Information Criteria to limit the number of lags used in the study. The optimal lag is found to be one in both cases.

Table 3 displays the results of the Granger causality tests from the vector autoregression model in Eq. (1). The null hypothesis is that row variables do not Granger-cause the variables in the column with the p-values of the test given in parentheses. The first column shows that the null hypothesis that call order imbalance does not Granger-cause index weekly returns is rejected. 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, have an effect on future index returns and vice-versa. The weekly index return has no predictive power on either of call or put order imbalance. Altogether, the results in Table 3 demonstrate that the main predictive power is from call options to index returns.

Fig. 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 order of the variables in the VAR model. Fig. 2 shows that a shock to call order imbalance leads to a significant decrease of −19.23 bps in the week ahead and a cumulative decrease of −17.95 bps in the five weeks ahead, confirming the Granger causality test results. On the other hand,

Table 3

This table presents Granger causality tests and correlation of residuals based on the vector autoregression model in Eq. (1): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return, Call OIB, Put OIB, VBI, Govt Bond, Term Spread}]'$. 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.

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)	

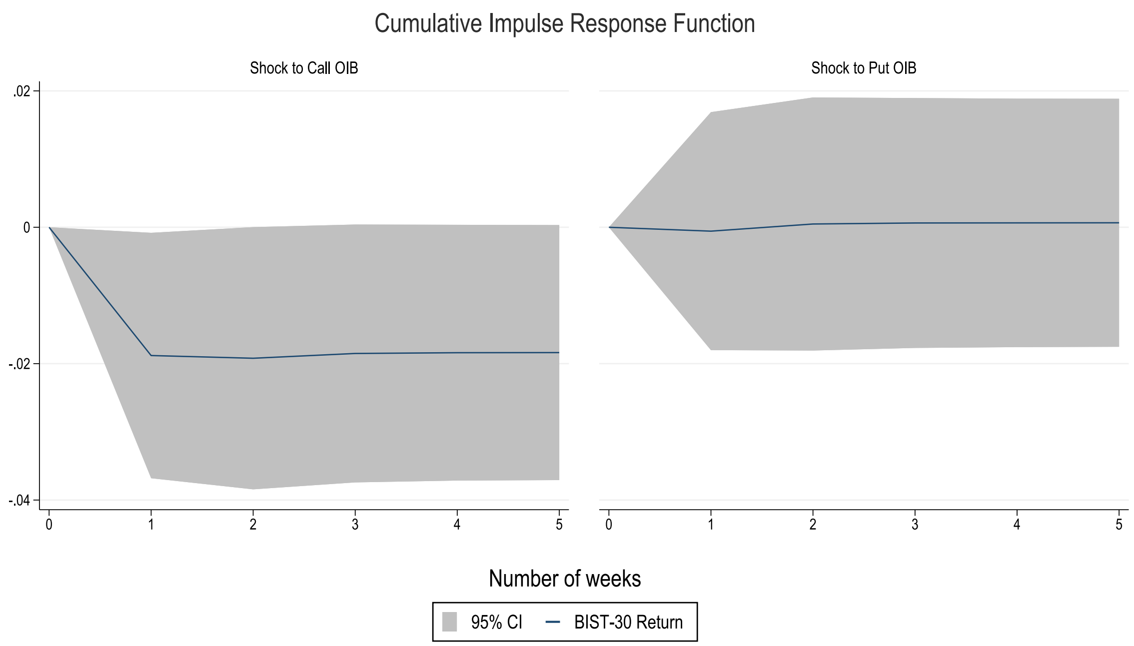

Fig. 2. Cumulative impulse response functions (with 95% confidence intervals) of call and put order imbalance to the BIST-30 index returns up to 5 weeks ahead.

there is no significant impact of put order imbalance on index returns. The results suggests that an increase in the volume of long calls or a decrease in volume of call writing forecasts a decrease in next-week index returns. Generally, the results demonstrate the predictive power of options market on the spot returns in our sample market.

4. Additional tests

4.1. Effect of stock order imbalance and futures order imbalance

Several studies focused on the effect of order imbalance in equity markets, including Chan and Fong (2000), Chordia et al. (2002), Chordia and Subrahmanyam (2004), and Zhang, Jiang, and Zhou (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 stock market can have impact on price dynamics. Hu (2014) highlights that stock order imbalance can predict stock returns either temporarily or permanently. The author claims that 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, it is possible that the predictive effect revealed in the previous section is 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 (Cao, Chen, & Griffin, 2005; Chan et al., 2002) whereas some others find that stock order flow has no predictive power on index returns (Chordia et al., 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 futures market can also have an effect on the underlying asset return through the transfer of order imbalance from futures market to stock market (Lee, Ryu, & Yang, 2021). The sustenance of the negative predictability of call order imbalance would demonstrate that 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 in the German market. Lee et al. (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 impact on spot index returns. One variable is the index futures contracts imbalance computed as 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:

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

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

Table 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 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 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, put, futures and stock order imbalance and other macroeconomic indicators. Likewise, the residual in the VAR equation where call order imbalance is the dependent variable represents the part of the call order imbalance that is not explained by lagged call, put, 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.

[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, 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.

[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 4
This table presents Granger causality tests and correlation of residuals based on the vector autoregression model in Eq. (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 = [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.

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)	

We also find that the futures order imbalance has no predictive power on the equity market index returns. This result shows that 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 futures market (Ryu, Ryu, & Yang, 2021). We do not find that index futures lead index options market, neither does options market 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 imply that neither of stock order imbalance nor futures order imbalance have price impact on the underlying spot next-week index returns.

4.2. Role of delta-weighted order imbalance

As it is the nature of options market, the spot index market underlies multiple option contracts. Investors choose option contract 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, which is 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

Table 5
This table reports the parameter estimates and p-values of Granger causality tests in parentheses based on the vector autoregression model in Eq. (3): $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t$, where $y_t = [\text{BIST-30 Return}, \delta_{\text{Call OIB}}, \delta_{\text{Put OIB}}, \text{VBI}, \text{Govt Bond}, \text{Term Spread}]'$. 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.

	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)

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 higher delta-weighted option imbalance, there is greater pressure on investors to delta-hedge their option exposure in the underlying market (Holowczak, Hu, & Wu, 2014).

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

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t, \tag{3}$$

$y_t = [\text{BIST-30 Return}_t, \delta_t^{call}, \delta_t^{put}, \text{VBI}_t, \text{Govt Bond}_t, \text{Term Spread}_t]'$, 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 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 Eq. (2). We find that 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 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.

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 Eq. (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 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 counterparties is the driver of 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 counter-party (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 reversal in spot index price (positive next-week return) towards the fundamental level as the price pressure reduces.

4.4. Effect of GDP announcements

To further understand which of 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 et al. (2021), informed investors using index options rely on their sophistication and pace to

Table 6
This table presents the parameter estimates and the p-value of the Granger causality tests in parentheses based on the vector autoregression model in Eq. (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 $y_t = [\text{BIST-30 Return}, \text{Call OIB}, \text{Put OIB}, \text{VBI}, \text{Govt Bond}, \text{Term Spread}]'$. Call order imbalance (Call OIB) is segregated into positive (Call OIB$^+ = max(0, \text{Call OIB})$) and negative (Call OIB$^- = min(0, \text{Call OIB})$) components. Put order imbalance (Put OIB) is segregated into positive (Put OIB$^+ = max(0, \text{Put OIB})$) and negative (Put 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.

	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)	

Table 7
This table reports the parameter estimates and p-value of Granger causality tests in parentheses based on the vector autoregression model in Eq. (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 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 bond. 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 ×Call OIB and GDP ×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.

	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 ×Call OIB	0.072 (0.112)	0.066 (0.318)
GDP ×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)

trade on newly released macroeconomic information. To evaluate the nature of the predictive power of option 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 7 displays the result of this specification. GDP announcement is classified as positive (negative) surprise if the actual GDP announced by the central bank is higher (lower) than the investor consensus before announcement as obtained from Bloomberg database.

According to Table 7, the call order imbalance is negative and significant while the interaction term GDP × Call OIB is positive and insignificant for weeks of positive and negative GDP news announcement. The implication of this result is that the hedging-based view continues to dominate 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]

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 and put order imbalance, respectively. An increase in call (put) order imbalance implies that there is higher call (put) buy pressure in the option market. According to the information-based view, there will be a persistence in the direction of relationship between innovations to option order imbalance and spot returns. However, reversal

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

Table 8

This table reports the parameter estimates and p-values of Granger causality tests in parentheses based on the vector autoregression model in Eq. (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.

	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)	

of direction supports the hedging-based view that increase in option buy pressure leads to a transfer of temporary price pressure to spot market. We run the following vector-autoregression model to examine the nature of predictability present in our sample market:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \epsilon_t \tag{4}$$

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 $i \in 1, \dots, p$ are (6×6) matrices, and ϵ_t are (6×1) vectors of error terms.

The results as displayed in Table 8 indicate that increase in call option order imbalance predicts negative next-week spot index return at 1% significance level, consistent with earlier result. Shocks to call order buying pressure is reflected in the underlying stock market. In weeks of increased demand pressure on options, counterparties are forced to increase their hedging demands in the stock market, further driving the relationship.

5. Conclusion

We investigate the linkages between index options market and the underlying benchmark index for one of the most popular emerging markets, Turkey. The analysis, which covers the period between March 2017 and June 2020, shows that trading in the options market has significant effect on contemporaneous and future weekly spot index returns. In particular, an increase in buying pressure relative to selling pressure on call options leads to a higher contemporaneous weekly open-to-close index returns with a significant reversal causal effect in the following week. Unlike the information-based view that predicts that order imbalance leads to a permanent effect on price movements, the results in this paper is in support of 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 et al. (2005), and Hu (2014) who argue that option 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 in this study have implications for future research. First, various studies have shown that different investor types (such as 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., Bae and Dixon (2018), Kuo, Chung, and Chang (2015)). 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 et al. (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 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 the price discovery and market efficiency in the spot market.

CRediT authorship contribution statement

Ahmet Sensoy: Conceptualization, data curation, Writing – original draft, Writing – review & editing, Supervision. **John Omole:** Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing.

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