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The Impact of Fundamental Shocks on Stock Prices: Evidence from Turkey

Mercan Hatipoglu[1,*], Nurullah Uckun[1] & Serkan Terzi[2]

[1]Dept. of Management, Eskisehir Osmangazi University, Eskisehir, Turkey

[3]Dept. of Management, Cankiri Karatekin University, Cankiri, Turkey

*Corresponding author: Dept. of Management, Eskisehir Osmangazi University, PO Box 26480, Eskisehir, Turkey. Tel: 90-222-239-3750-1749 E-mail: mercanhatipoglu@gmail.com

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Abstract

In this study, we investigate the relationships between Borsa Istanbul Stock Exchange (BIST) stock prices and underlying macroeconomic shocks in the Turkish economy. For this, we employ both bivariate and trivariate Structural Vector Autoregressive (SVAR) models to examine the effects of fundamental shocks on stock price movements in Turkey during the period 1998-2013. The analysis reveals that the relationship between stock prices and real activity variables is substantially stronger than the relationship between stock prices and key investments, i.e., the interest rates, gold investment and the US dollar. Furthermore, most of the findings in this paper cannot confirm that fundamental shocks became substantially less important.

Keywords: macroeconomic shock; structural vector autoregressive model; Turkey

1. Introduction

Structural Vector Autoregressive (SVAR) models are frequently used to detect a relationship between stock markets and macroeconomic fundamentals because these models enable an analysis of how asset prices respond to macroeconomic fundamentals shocks. The use of the SVAR approach encounters some restrictions imposed by finance or economic theory in defining these shocks. Sources of shocks can stem from fluctuations in macroeconomic variables such as interest rates, GDP, foreign exchange, inflation, oil prices, dividend or changes in monetary and fiscal policy. Recent contributions in this area were made by Jacobs et al. (2003), Aarle et al. (2003), Golinelli & Rovelli (2005), Ravnik & Žilić (2011), and Afonso & Sousa (2012) who employed SVAR models to analyze fiscal and monetary shocks. However, Campbell & Ammer (1993), Binswanger (2004), Huang & Guo, (2008), Laopodis (2009), and Jean Louis & Eldomiaty (2010) employed the SVAR approach to investigate whether economic fundamentals play an important role in stock markets. In addition, some papers focusing on macroeconomic fundamentals utilized the oil prices. Kapusuzoğlu (2011) stated there was a cointegrated relationship between the BIST-100 Index and Brent oil prices during the period April 1, 2000 and April 1, 2010. Additionally, Kapusuzoğlu (2011) stated there was a one-way causality relationship between the the BIST-100 Index and oil prices. Many studies use exchange rate as a proxy for macroeconomic shocks. Pekkaya & Bayramoğlu (2008) found that there is Granger causality between the BIST- 100 index and the US dollar exchange rate for the period of 1990-2007.Dogru&Recepoglu (2013) conducted linear co-integration tests and found that there is a co-integration relationship between exchange rates and the BIST- 100 index in the long run using monthly time-series data covering the time period 1980 - 2013.Many papers use various macroeconomic variables to examine which factors have significant impacts on stock returns. Kaya et al. (2012) employ the ordinary least squares method of multiple regression models to investigate the relationship between macro economic variables and BIST-100 Index returns. They found a positive relationship between stock returns and money supply (M2) and a negative relationship with the exchange rate. Consistent with the existing literature, Acikalin et al. (2008) found a long-term stable relationship between ISE and four macroeconomic variables, i.e., GDP, exchange rates, interest rates, and current account balance. Some studies concerning the relationship between monetary policy and stock prices have used SVAR models. Akay & Nargelecekenler (2009) found that contractionary monetary shocks have the temporary effect of interest rate increases in both the short run and the long run and thus causes to decrease in BIST-100 index stock prices.

In this paper, we investigate the relationship between real economic variables and real stock returns during the 1998 - 2001 period employing various SVAR models for Turkey. Subsequently, we compare the results of the SVAR models based on forecast error variance decompositions over the full period. Fundamentals are essential for stock markets because the instrict value of a firm’s stock depends on the discounted value of its cash flows. Because the present value of cash flows affected by variables such as interest rates, inflation and GDP variables, any movement in these variables can be utilized to determine the changes in expected value of future cash flows (Laopodis, 2009).

There are impressive reasons to focus on BIST-100 Index which is used as the main index for BIST Equity Market in Turkey. First of all, Turkey has overcome a series of economic problem in recent years and is currently maintaining stable economic growth. For example the year-on-year GDP growth accelerated to 3% in the first quarter of 2013. Additionally Turkey's economy grew 8.5 % in 2011;, this was the second biggest growth rate in the world after China. According to the OECD, Turkey will be the fastest growing economy among OECD members during the 2012-2017 period, with an average annual growth rate of 5.2 %. Today, Turkey is an upper-middle income country that has a population of 75 million and a gross domestic product of US$735 billion, making it the 16th largest economy in the world (World Bank, 2013).Moreover, market capitalization of companies traded on the BIST reached TL 550,051 million (US$ 309,644 million) by the end of 2012 from a total of TL 381,152 million (US$ 201,924 million) in 2011 year end (CMB, 2012).Table 1 shows the medium-term macroeconomic projections and targets estimated by the Word Bank.

Table 1. Medium-Term Macroeconomic Projections and Targets

Year	2012	2013	2014	2015	2016
Growth (%)	2.9	4	5	5	5
CPI Inflation (%) (end-of-period)	7	5.2	5	5	5
Public Sector Primary Balance/GDP %	1.3	1.1	1.4	1.7	1.9
Gross Public Debt/GDP(Note 1)	38.4	37	35.2	33.2	31.2
Gross External Debt/GDP	42.6	43	42.6	41.8	41.1
CAD (billion US$)	63.7	66	66.4	64.9	61.1
CAD/GDP (%)	7.6	7.3	6.9	6.3	5.6
Reserves (billion US$) (including gold)	90.4	91.9	95.1	97.1	100.8

Source: World Bank Staff Projections

The remainder of the paper is organized as follows. In Section 2, we describe the methodology and the data. Section 3 presents the result of the SVAR models. Section 4 presents concluding remarks.

2. Data and SVAR Methodology

In this paper, the following data are used: US dollar, gold prices, interest rates, the leading indicators index, real GDP and BIST-100 index. While the US dollar, gold and interest rates are intended to be alternative financial investment tools with respect to the BIST-100 Index, real GDP and the leading indicators index are assumed to predict cyclical turning points of Turkish economic activity. The BIST-100 index deflated by the GDP deflator, serves as the real stock price measure. The nominal interest rate quarterly data of over-night interbank interest rates represents the interest rate and GDP is seasonally adjusted. We consider bivariate and trivariate SVAR models that are composed of the first difference log of the real stock prices indexes, the first-difference log of gross domestic products, the first-difference log of US dollar prices, the first-difference log of gold prices, the first-difference log of leading indicator for Turkish economy and the interest rate level. Quarterly data are obtained from the Central Bank of the Republic of Turkey (CBRT) electronic data delivery system and the estimation period was from Q1-1998 to Q1-2013. The descriptive statistics for all six variables in log levels are presented in Table 2.

Table 2. Descriptive Statistics

	LNBIST100	LNUSD	INT	LNGDP	LNGOLD	LNLEAD
Mean	10.87	6.46	21.04	16.90	3.02	5.03
Median	10.97	0.58	15.25	16.93	3.01	5.06
Maximum	11.49	14.31	70.00	17.22	4.59	5.34
Minimum	10.02	0.16	1.500	16.62	0.75	4.56
Std. Dev.	0.37	6.66	18.26	0.19	1.07	0.21
Skewness	-0.41	0.17	0.97	0.02	-0.43	-0.31
Kurtosis	2.05	1.05	2.73	1.56	2.36	2.00
JarqueBera	4.04	9.98	9.82	5.27	2.96	3.53
Probability	0.13	0.00	0.00	0.07	0.22	0.17

SVAR models have also recently been applied to many financial variables in different frequency and different time periods. As a result, it is difficult to compare all models that include different variables.

SVAR models treat all variables as endogenous and decompose all variables into their expected and unexpected parts. The identifying restrictions are then imposed only on the unexpected part because the models assume that nonfundamental shocks have no long-run effects on fundamental variables. Briefly, SVAR models impose identifying restrictions on VAR models to infer structural shocks from them.

In this paper, we consider bivariate and trivariate SVAR models that comprise the firs-t difference log of real stock prices, p, and the first-difference log of other fundamental variables, which are denoted x and y, respectively. All variables are provide to be (I) with respect to the Augmented Dickey–Fuller unit test. Table 3 presents the result of unit root tests for all variables. We demonstrate that there is no co-integrating relationship between the variables included in the VAR, because a VAR composed first-differences would otherwise be biased statistically.

Table 3. Unit Root Tests (ADF) Result

	Level				First -Differences			
	%1	%5	%10	t-stat	%1	%5	%10	t-stat
LNBIST-100	-4.12	-3.48	-3.17	-3.14	-4.12	-3.48	-3.17	-4.89
LNUSD	-4.11	-3.48	-3.17	-1.92	-4.12	-3.48	-3.17	-7.57
INT	-3.54	-2.91	-2.59	-2.18	-3.54	-2.91	-2.59	-16.80
LNGDP	-4.12	-3.48	-3.17	-2.68	-4.12	-3.48	-3.17	-5.98
LNGOLD	-4.12	-3.48	-3.17	-2.26	-4.12	-3.48	-3.17	-6.33
LNLEAD	-4.11	-3.48	-3.17	-3.46	-4.12	-3.48	-3.17	-7.02

Presenting the bivariate SVAR model in a matrix notation showed the following equation:

$$\begin{bmatrix} \Delta x_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} R_{11(L)} & R_{12(L)} \\ R_{21(L)} & R_{22(L)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (1)$$

In equation 1, $R_{ij}(L)=\Sigma_{k=0}^{\infty} r_{ij}(k)L^k$ for i, j=1,2 are the infinite polynomials in the lag operator L. Blanchard and Quah (1989) proposed an identification method based on restrictions on the long-run properties of the impulse responses.The (accumulated) long-run response to structural innovations takes the following form:

$$C=\Psi_\infty A^{-1}B \quad (2)$$

A and B are matrices to be estimated and $\Psi_\infty=[I-L_1-\ldots\ldots L_p]$ is the estimated accumulated responses to the reduced form shocks.Long-run restrictions are identified in terms of the elements of this C matrix, especially in the form of zero restrictions.The restriction C_{ij} means that the (accumulated) response of the i-th variable to the j-th structural shock is zero in the long-run.

To specify long-run restrictions in a matrix, e.g., describing bivariate SVAR models economic theory suggests that we restrict the long-run response of the shock of second the endogenous variable to the first variable to be zero $R_{12}=0$.

Then the long-run response matrix can be written as:

$$\begin{bmatrix} R_{11} & 0 \\ R_{21} & R_{22} \end{bmatrix} \quad (3)$$

This matrix enable to us to specify the shocks ε_1, ε_2, fundamental and nonfundamental, respectively. However the trivariate SVAR model can be written as:

$$\begin{bmatrix} \Delta x_t \\ \Delta y_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} R_{11(L)} & R_{12(L)} & R_{13(L)} \\ R_{21(L)} & R_{22(L)} & R_{23(L)} \\ R_{31(L)} & R_{32(L)} & R_{33(L)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \quad (4)$$

$R_{12}(1)= R_{13}(1)= R_{23}(1)= 0$,

According to the trivariate SVAR model $\varepsilon_1, \varepsilon_2$ are fundamental shocks and ε_3 are nonfundamental shocks.

SVAR models must provide some conditions. First the estimated SVAR must be stationary and all roots must lie inside the unit circle otherwise, the estimated results are not valid. Second, the model must not be heteroscedastic the parameter will be inefficient. Finally model shouldn't suffer from autocorrelation. If the residuals are correlated, the standard errors tend to be underestimated or overestimate. Based on the results of the Akaike information criterion and the Schwarz criterion, we employ enough lags for all estimates to avoid residual autocorrelation and heteroscedasticity.

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3. Empirical Evidence

Before the SVAR models, we conduct cointegration tests using Johansen's (1991) approach under the assumption of a linear deterministic trend in the data. In section two, Augmented Dickey–Fuller unit root test demonstrate that all variables are stationary (I) in first-differences and non-stationary in level. According to Johansen (1991) if the variable is integrated in the same order, long-run relationship exists. Consequently cointegration analysis used to examine whether any long run relationship exists between the variables. If the variables are found to be co-integrated, then the vector error correction model (VECM) model must be employed for variance decomposition instead of SVAR models. Tables 4 and 5 summarizes the results of unrestricted cointegration rank tests for bivariate and trivariate models respectively.

Table 4. Johansen Cointegration Tests of Bivariate Models

	I. Model	II. Model	III. Model	IV. Model	V. Model	
	Trace Statistics	*Trace Statistics*	*Trace Statistics*	*Trace Statistics*	*Trace Statistics*	*Critical* Value*
None	13.25	13.82	13.20	15.23	13.30	15.49
At most 1	5.68	0.15	3.12	3.65	1.29	3.84
	Max-Eigen Statistic	*Max-Eigen Statistic*	*Max-Eigen Statistic*	*Max-Eigen Statistic*	*Max-Eigen Statistic*	*Critical** Value*
None	7.56	13.67	10.07	11.57	12.01	14.26
At most 1	5.68	0.15	3.12	3.652	1.29	3.841

* Trace test indicates no cointegration at the 0.05 level

** Max-eigenvalue test indicates no cointegration at the 0.05 level

Table 5. Johansen Cointegration Tests of Trivariate Models

	VI. Model	VII. Model	VIII. Model	
	Trace Statistics	*Trace Statistics*	*Trace Statistics*	*Critical* Value*
None	22.36	22.08	27.00	29.79
At most 1	7.45	10.61	7.35	15.49
At most 2	1.62	2.012	2.28	3.84
	Max-Eigen Statistic	*Max-Eigen Statistic*	*Max-Eigen Statistic*	*Critical** Value*
None	14.91	11.47	19.65	21.13
At most 1	5.82	8.59	5.06	14.26
At most 2	1.62	2.01	2.28	3.841

* Trace test indicates no cointegration at the 0.05 level

** Max-eigenvalue test indicates no cointegration at the 0.05 level

We employ bivariate and trivariate SVAR models. The data sets used for these models are the quarterly series of the selected variables from Q1:1998 to Q3:2013. Table 6 presents the bivariate and trivariate SVAR models.

Table 6. Bivariate and Trivariate SVAR Models

Bivariate and Trivariate SVAR models		
I.	Model: y=BIST-100,	x_1=interest rate
II.	Model: y=BIST-100,	x_1= GDP
III.	Model: y=BIST-100,	x_1=leading indicator
IV.	Model: y=BIST-100,	x_1=gold
V.	Model: y=BIST-100,	x_1=US dollar
VI.	Model: y=BIST-100,	x_1=US dollar, x_2= gold
VII.	Model: y=BIST-100,	x_1=US dollar, x_2= interest rate
VIII.	Model: y=BIST-100,	x_1=US dollar, x_2= leading indicator

Models I to V are bivariate models that comprise BIST-100 stock prices and one fundamental variable, E.G., the indicator of real activity (GDP or leading indicators) or an investment alternative (US dollar or gold). The trivariate models V to VIII include real interest rates, gold, and leading indicator in addition to the US dollar. In the bivariate and trivariate models, BIST-100 index's own lag indicates nonfundamental shock, and the other variable means indicate fundamental shock. The result of the stock price forecast error variance decompositions are presented in Tables 7 to 14, respectively.

Table 7. Stock Price Forecast Error Variance Decomposition Model I and -Model II

	Model I		Model II	
Period	Fundamental Shocks	Nonfundamental Shocks	Fundamental Shocks	Nonfundamental Shocks
1	31.51	68.48	77.65	22.34
2	29.08	70.91	68.77	31.22
3	29.44	70.55	67.96	32.03
4	29.32	70.67	68.00	31.99
5	29.36	70.63	67.99	32.00
6	29.35	70.64	67.99	32.00
7	29.36	70.63	67.99	32.00
8	29.36	70.63	67.99	32.00
9	29.36	70.63	67.99	32.00
10	29.36	70.63	67.99	32.00

According to Table 7, while GDP shocks explain more than 60% of the forecast error variance, interest rate shocks explain nearly 30 % of the forecast error variance. One of the reasons for this variance may be the decreasing interest rates since 2002 in the Turkish economy. During the period 2002-2013, Central Bank of the Republic of Turkey interest rates drop to 3.50% from 57%. Consequently, the deposit rates for banks and bond rates are not perceived as alternative investment tools in Turkey by investors.

Table 8. Stock Price Forecast Error Variance Decomposition Model III and -Model IV

	Model III		Model IV	
Period	Fundamental Shocks	Nonfundamental Shocks	Fundamental Shocks	Nonfundamental Shocks
1	29.45	70.54	13.41	86.58
2	33.30	66.69	11.55	88.44
3	31.11	68.88	11.29	88.70
4	30.60	69.39	11.26	88.73
5	31.76	68.23	11.25	88.74
6	32.29	67.70	11.25	88.74
7	31.60	68.39	11.25	88.74
8	31.57	68.42	11.25	88.74
9	32.04	67.95	11.25	88.74
10	32.24	67.75	11.25	88.74

Gold shocks explain 11% on average, of the forecast error variance, and 30% of variance is attributable leading indicators. Because of significant fluctuations and drops in gold prices, some household investment choices shift to other financial tools. Because leading indicators are proxies for the economic activity, investors will monitoring the market developments in Turkey.

Table 9. Stock Price Forecast Error Variance Decomposition Model V

Period	Fundamental Shocks	Nonfundamental Shocks
1	1.98	98.01
2	1.79	98.20
3	1.76	98.23
4	1.76	98.23
5	1.76	98.23
6	1.76	98.23
7	1.76	98.23
8	1.76	98.23
9	1.76	98.23
10	1.76	98.23

The US dollar is generally considered a very valuable financial instrument for investors in Turkey. An unexpected result is that approximately 1% of variance is attributable to the US dollar.

Table 10. Stock Price Forecast Error Variance Decomposition Model VI

Period	Fundamental Shocks	Fundamental Shocks	Nonfundamental Shocks
1	13.42	0.14	86.42
2	11.56	0.16	88.26
3	11.30	0.16	88.52
4	11.27	0.17	88.55
5	11.27	0.17	88.55
6	11.26	0.17	88.55
7	11.26	0.17	88.55
8	11.26	0.17	88.55
9	11.26	0.17	88.55
10	11.26	0.17	88.55

Model VI shows that if gold and the US dollar are included in a trivariate SVAR model as a alternative investment tools, both types of shocks only capture a very small fraction of the forecast error variance.

Table 11. Stock Price Forecast Error Variance Decomposition Model VII

Period	Fundamental Shocks	Fundamental Shocks	Nonfundamental Shocks
1	5.68	48.45	45.85
2	5.06	44.93	49.99
3	8.98	42.91	48.10
4	9.83	42.26	47.89
5	11.33	40.62	48.03
6	10.81	40.69	48.49
7	10.87	40.34	48.77
8	11.11	40.19	48.69
9	11.43	40.00	48.55
10	11.48	39.94	48.57

In model VII, the US dollar and interest rate almost increases the decomposition of forecast error variance in stock prices that is explained by fundamentals.

Table 12. Stock Price Forecast Error Variance Decomposition Model VIII

Period	Fundamental Shocks	Fundamental Shocks	Nonfundamental Shocks
1	54.80	1.49	43.70
2	64.58	1.24	34.16
3	63.55	2.94	33.50
4	63.22	3.13	33.64
5	63.27	3.14	33.58
6	63.28	3.16	33.54
7	63.28	3.17	33.54
8	63.28	3.17	33.54
9	63.28	3.17	33.54
10	63.28	3.17	33.54

After combining the US dollar with the leading indicators, the decomposition of forecast error variance in stock prices explained by fundamentals is significantly increased, when compared to a bivariate model that only includes the US dollar.

4. Conclusion

Many studies have been conducted to provide the empirical evidence about the relationship between stock returns and macro-economic variables in emerging markets to fundamantal and nonfundamental shocks is narrow. This paper sheds light on the existence of fundamentals shocks between stock prices and various macroeconomic variables based on the quarterly observations of GDP, the leading indicators index, the US dollar, gold, interest rates and the stock price index in Turkey.

In this paper we employed bivariate and trivariate structural vector autoregressive models with the US dollar, gold, interest rates, the leading indicators index, real GDP and the BIST-100 index to investigate the role of fundamentals on stock prices in Turkey. The results demonstrate that GDP and the leading indicators index better explain stock price dynamics than do the US dollar, gold and interest rates. These findings suggest that relationship between stock prices and real activity variables is substantially stronger than the relationship between stock prices and key investments, e.g., interest rates, gold and the US dollar. Furthermore, fundamental shocks are more important than nonfundamental shocks in explaining stock price movements in our trivariate models except in model VI with the US dollar and gold. Finally, most of the findings in this study could not confirm that fundamental shocks became substantially less important. These findings may have important implications for diligent investors who want to seek profitable opportunities in emerging stock markets. According to our results, investors should consider the rapidly changing price dynamics of the Turkish capital market. The results also suggest that investors should consider real activity variables rather than alternative investment tools. Future research should be directed toward a more detailed investigation into the impacts of fundamental shocks on emerging markets.

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Note

Note 1. World Bank staff estimates for total public debt and gross external debt stockstock are consistent with EU defined general government debt stock reported in MTP.. Source: World Bank Staff Projections

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