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# INTERNATIONAL TRANSFER OF PRICING INFORMATION BETWEEN DUALLY LISTED STOCKS

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## Abstract

International multiple listing offers a unique opportunity to study the efficiency of information transmission across national markets. The knowledge gained from observing a stock of the same company priced in multiple markets differs from what may be gained from observing relations across markets of aggregate price indices. We investigate five companies based in Israel whose stocks are listed on both the Tel Aviv Stock Exchange and NASDAQ. Our empirical tests of causality in price changes use the side-by-side Box-Jenkins ARIMA models and the Sims VAR model. Overall, the results show that price causality in dually listed stocks is unidirectional from the domestic market to the foreign market.

## I. Introduction

Recent years have witnessed the proliferation of stocks listed in multiple markets around the world. Multiple listing offers a unique opportunity to study the transmission of pricing information across markets. The knowledge gained from observing the same stock priced in multiple markets differs from what may be gained from observing relations of aggregate price indices across markets.

Studying U.S. companies whose stocks are dually listed domestically and abroad, Neumark, Tinsley, and Tonsini (1991) find that the foreign market reacts to domestic price changes more quickly than the domestic market reacts to foreign price changes. This asymmetry, confirmed for price indices by Eun and Shim (1989) and Hamao, Masulis, and Ng (1990), is interpreted by Garbade and Silber (1979a) as evidence that the foreign market acts as a satellite to the domestic market. Chowdhry and Nanda (1991) show that when a security is traded in several markets, informed traders have greater opportunities to exploit private information. They further show that the expected return of informed traders is diminished by a timely transmission of pricing information to satellite markets—a phenomenon that may be caused by competing market makers who offer to the general public pricing information at reduced costs. Khan, Baker, Kennedy, and Perry (1993), who estimate the effect of dual listings on shareholder wealth, find a negative return and a change in market structure—evidence that dual listing may be motivated by factors other than shareholder-wealth maximization.

We investigate the transmission of pricing information for stocks based in Israel that are listed on both the Tel Aviv Stock Exchange (TASE) and the U.S. NASDAQ. As Neumark, Tinsley, and Tosini (1991) and Lau and Dilitz (1994) argue, the study of individual stocks traded in two markets offers a unique opportunity to compare the efficiency of the two trading mechanisms since, in the absence of arbitrage opportunities, the risk-return characteristics of each of these stocks should be the same in the two markets. Indeed, finding a causal price linkage between the two markets would raise the possibility of market and intermarket inefficiencies with possible arbitrage opportunities. The question of market efficiency remains at the core of the multiple-listing phenomenon. Both increased efficiency and international multiple listing appear to be rooted in the parallel economic and political developments of recent years: increasing volume of international trade, increasing integration of national economies, growing power of multinational corporations, advancing information technology, expanding choice of financial products, liberalizing financial markets and foreign exchange restrictions, and increasing uniformity of listing requirements and trading mechanisms across major capital markets.

We use two alternative models to generate the forecasting errors of stock returns required for causality tests. One is the autoregression moving average (ARIMA) model developed by Ashley, Granger, and Schmalensee (1980) for testing for Granger's (1969) causality after identifying the statistical properties of the price time series using the Box-Jenkins (1970) techniques. In the absence of a well-developed theory for this model, and since our results could be sensitive to the identification of the ARIMA model, we also apply the vector autoregression (VAR) model developed by Sims (1980). This model employs a fundamentally different test that allows independent assessment of the robustness of our findings. Results based on in-sample data show price causality and reversed causality between the two markets. However out-of-sample data show weak unidirectional causality from the domestic market to the foreign market. Our interpretation of the results is that price causality in dually listed stocks is unidirectional from the domestic market to the foreign market.

## II. Testing Methodology

We use the ARIMA model first. Ashley, Granger, and Schmalensee (1980) argue that causality tests should rely primarily on out-of-sample performance of forecasting models. They recommend the Box-Jenkins (1970) techniques as suitable for identifying the statistical properties of the underlying time series. We then use the VAR model (Sims (1990)). We rely on two models to reduce the possibility of conclusions that depend heavily on the validity of a single estimated time series process. Both models are suitable for forecasting where a well-developed theory is absent. The ARIMA model offers the ability to capture information that is hard to identify in structural models. As pointed out by Lupolleti and Webb (1986), computation of ARIMA forecasts requires judgment in identifying the model, while the VAR model requires almost none since the forecasting errors are generated by a simple regression analysis. The VAR model can also test for multivariate interaction among several variables. Lupolleti and Webb find that, despite apparent differences, no one of the two models is systematically superior.

For out-of-sample tests, we use the ARIMA model to estimate the stochastic process in each market based on in-sample observations at $T = 0, \ldots, t$. The estimated parameters are then used to forecast share prices at $T = t+1, t+2, \ldots, n$, in the other market. A significant relation between share prices across markets would indicate a causal relation. The underlying assumption is that tests based on in-sample data essentially measure goodness of fit, and that the more powerful tests rely on the ability to forecast future prices.

The VAR model is based on estimating the response function of a pre-identified system of equations to a particular random shock. The response enables us to trace the reaction of the share price in one market to unexpected future developments in one of the two markets. We identify the parameters of the VAR model based on $T = 0, \ldots, t, \ldots, n$ and test for causality by introducing to the system a shock that is equal in size to the return standard deviation. The underlying assumption is that if price changes on the TASE tend to precede price changes of the same stock on NASDAQ, the price shock introduced will be subsequently observed on NASDAQ.

Our search for causality raises the issue of cointegration. The possibility of cointegration is suggested by a scenario of two parallel price time series for dually listed stocks, reflecting the same economic value in two markets. When the two time series are linearly combined they may become nonstationary. Engle and Granger (1987) argue that cointegration should be tested for before testing for causality. If the time series are cointegrated across markets, the empirical models would require an error-correction mechanism. In the following subsections we formally describe a test of cointegration followed by the two tests of causality.

*Cointegration Test*

Since cointegration would cause a misspecification of tests based on ARIMA and VAR models, we determine whether our two sets of variables combined linearly are cointegrated. Following Engle and Granger (1987), we test for cointegration by the regressions

$$Y_t = \alpha + \beta X_t + \epsilon_t \tag{1}$$

$$\epsilon_t - \epsilon_{t-1} = -b\epsilon_t + \Phi_t \tag{2}$$

where equation (2) is stated in an error-correction form to test the null hypothesis that the two time series are not cointegrated; i.e., $H_0$: $b = 0$. If $b$ is not significantly different from zero, $Y_t$ and $X_t$ are deemed not to be cointegrated. Like Engle and Granger, we use the Dickey-Fuller (1981) statistic to test this hypothesis.

*Ashley-Granger-Schmalensee Causality Tests*

The empirical tests presented in this section are based on Granger's (1969) definition of causality. Although standard causality tests compare the variances of in-sample forecasting errors, Ashley, Granger, and Schmalensee (1980) argue in favor of comparing the mean square of out-of-sample forecasting errors (MSE).[1] They suggest the following test of causality:

> $Y$ is said to cause $X$ if MSE($X,Y$) is significantly less than MSE($X$) where MSE($X$) is the population mean-square of the one-step forecasting errors of $X_{t+1}$ using a linear model based on $X_{t-j}$, and MSE($X,Y$) is the population mean-square of the one-step forecasting errors of $X_{t+1}$ using a linear model based on $X_{t-j}$ and $Y_{t-j}$ where $j = 0, 1, \ldots, n$.

They further suggest the following procedure to test for a significant difference between MSE($X$) and MSE($X,Y$). Let $\epsilon_1$ and $\epsilon_2$ be the respective forecasting errors of the univariate and bivariate models,[2] where $\delta_t = \epsilon_{1t} - \epsilon_{2t}$ and $\Sigma_t = \epsilon_{1t} + \epsilon_{2t}$. Then,

$$\text{MSE}(\epsilon_1) - \text{MSE}(\epsilon_2) = [\text{Cov}(\delta,\Sigma)] + [\mu^2(\epsilon_1) - \mu^2(\epsilon_2)] \tag{3}$$

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[1]Malliaris and Urrutia (1992) argue that Granger's (1969) causality essentially tests for the predictive ability of time series models. Ashley, Granger, and Schmalensee (1980) provide the rationale for placing a greater weight on out-of-sample forecasting in testing for causation.

[2]Under these definitions, the following relation holds:

$$\text{MSE}(\epsilon_1) - \text{MSE}(\epsilon_2) = [\text{Var}(\epsilon_1) - \text{Var}(\epsilon_2)] + [\mu^2(\epsilon_1) - \mu^2(\epsilon_2)]$$

where $\mu$ is the sample mean.

where the first term on the right-hand side is the covariance over the out-of-sample period. The MSE of the univariate model is said to be significantly greater than that of the bivariate model if the null hypothesis $\text{Cov}(\delta,\Sigma) = 0$ and $\mu(\delta) = 0$ is rejected against the alternative hypothesis that both values are nonnegative and at least one is strictly positive. They show that this is equivalent to testing the hypothesis $\alpha_0 = \alpha_1 = 0$ against the alternative hypothesis that both values are nonnegative and that at least one of them is strictly positive in the following simple regression:

$$\delta_t = \alpha_0 + \alpha_1[\Sigma_t - \mu(\Sigma_t)] + \Omega_t \tag{4}$$

The following five-step procedure is used to obtain the post-sample forecasts required for causality analysis:

1. Build separate univariate ARIMA models of $X$ and $Y$ using the Box-Jenkins (1970) procedure based on observations at $T = 0, \ldots, t$.
2. Compute from in-sample data the cross-correlograms between the resulting residuals for $k$ lags, where $r_k$ is the correlation coefficient between $\epsilon_{x_t}$ and $\epsilon_{y_{t+k}}$. If $r_k$ is significantly different from zero for $k > 0$, this tentatively indicates that $X$ causes $Y$. Conversely, if $r_k$ is significantly different from zero for $k < 0$, this tentatively indicates that $Y$ causes $X$.
3. For every tentative direction of causality, identify, estimate, and diagnostically check a bivariate model based on observations at $T = 0, \ldots, t$.
4. Initially form a univariate forecasting model for $X(t+1)$ based on $X(t-i)$ using $X(t+1) = f[X(t), X(t-1), X(t-2), \ldots] + e(X)$. Then, form a bivariate forecasting model for $X(t+1)$ based on $X(t-i)$ and $Y(t-i)$ using $X(t+1) = f[X(t), X(t-1), X(t-2), \ldots, Y(t), Y(t-1), Y(t-2), \ldots] + e(X,Y)$. MSE($X$) and MSE($X,Y$) are the mean-squared errors of $e(X)$ and $e(X,Y)$, respectively. Repeat this process to form parallel forecasting models for $Y(t+1)$ to test for reversed causality.
5. Use the univariate and bivariate models to generate one-step-ahead forecasts for $X$ or $Y$ in the post-sample period at $T = t+1, t+2, \ldots, n$, and compare the mean-squared forecasting errors of the two models.

*Causality Tests with the VAR Model*

Although the VAR model is not commonly viewed as a causality test, it allows prediction of stock prices based on their own lagged values and lagged values of other variables. Consistent results from the VAR model would add to the robustness of the results based on ARIMA tests. The ability to handle a multivariate analysis is an important advantage of the VAR model. A second advantage is that the ARIMA procedure relies on judgment in identifying the model, whereas the VAR model requires only identification of the lag structure of each time series and a simple multiple regression for estimation. A third advantage is that the VAR model treats out-of-sample tests as responses to innovations, which are based in turn on responses of a preidentified system of equations to a specific initial random shock in one of the variables computed from observations at $T = 0, \ldots, n$.

Based on the framework in Sims (1980), the unconditional VAR model is stated by:

$$\mathbf{Z}_t = \mathbf{A} + \Sigma_{j=1,k} \mathbf{B}_j \mathbf{Z}_{t-j} + \mathbf{e}_t \tag{5}$$

where $\mathbf{Z}_t$ is a $2\times1$ vector of percentage changes in share prices in the domestic or foreign markets; $\mathbf{A}$ and $\mathbf{B}_j$ are a $2\times1$ vector and a $2\times2$ matrix of coefficients, respectively; $k$ is a time lag; and $\mathbf{e}_t$ is a $2\times1$ vector of forecasting errors of the best linear prediction of $\mathbf{Z}_t$ based on the matrix $\mathbf{Z}_{t-j}$ of price changes in both markets. By successive substitution of the right-hand side of equation (5), this system of equations can be expressed as a moving average:

$$Z_t = \Sigma_{j=0,\infty} B_j e_{t-j} \tag{6}$$

This is a linear combination of current and past one-step-forward forecasting errors, labeled "innovations" by Sims (1980), where $B_j$ represents the response of variables in the system to an initial random shock in one of them.

These innovations allow us to view the reaction of a stock's current price in each market to unexpected future price changes of the same stock in either market. Since $e_t$ may be contemporaneously correlated, the VAR analysis requires a triangular orthogonalization. The initial random shock used is equal in size to one standard error of one variable. As shown by Eun and Shim (1989), when such a shock is introduced to the system, the remaining variables are also subject to a shock that is equal in size to their own standard deviation multiplied by their correlation with the first variable. Thus, if a stock's price changes on the TASE precede price changes of the same stock on NASDAQ, the effect would be reflected in subsequent price changes on NASDAQ. In such a case, a forecasting error will occur when future changes in a stock's price in one market are mostly influenced by price innovations of the same stock in the other market rather than by its own innovations. Sims (1980) measures the extent of influence of each variable by decomposing the variance of forecasting errors into the variances of forecasting errors explained by the two market variables.

## III. Data

*Sample*

The sample consists of more than 6,000 daily closing prices of five stocks of Israeli-based companies dually listed on the TASE and NASDAQ. These data include all trading days from July 1988 to September 1993, a period selected to avoid direct effects of the U.S. market crash in October 1987 (Maliaris and Urrutia (1992)) and the Israeli market crash in February 1994. Additional data for the same period include daily figures of the TASE value-weighted general index and the equally weighted NASDAQ index. Share prices in the TASE are restated in U.S. dollars based on the daily spot exchange rate. During the sample period, almost sixty Israeli companies were listed in the U.S., mostly on NASDAQ, seven of which were also listed on the TASE. Of those, only five had sufficient data to be selected for this study. They are Teva, Elbit, Elron, Robotec, and Aryt, of which only Teva was listed as ADR (sponsored).

*Exchange Rates*

Daily closing stock prices in Tel Aviv are expressed in dollars using the noon-time spot exchange rate determined and published daily by the country's Central Bank. The potential issues raised by using that exchange rate concern its synchronization with closing stock prices and its relevance as a market price. Both issues do not appear to interfere with our results because the same rate is used by all Israeli banks and in most foreign exchange transactions throughout the day.[3] Moreover, most investors in the stocks studied are Israelis who can legally buy and sell foreign currency only in Israeli banks and therefore only at the same rate. The insignificance of these issues is further suggested by evidence that the annual standard deviation of daily percentage changes in the exchange rate during the sample period was less than 7 percent, and its correlation with daily stock returns was close to zero. These arguments notwithstanding, in view of the important influence exercised by Israel's Central Bank over the exchange rate, we recalculated the results using alternatively the spot exchange rates of the previous and following day. The results were virtually unchanged.

*Trading Time Difference*

Trading hours on the TASE and NASDAQ do not overlap. Using Eastern Standard Time as reference, the TASE is open between 3:30 a.m. and 9:30 a.m., and

[3]The Central Bank buys foreign currency from Israeli banks or sells it to them daily in an amount equal to their aggregate excess demand or supply. The exchange rate set (and used in this study) is the one that clears the market that day.

NASDAQ is open between 9:30 a.m. and 4:00 p.m. Special care must be taken when testing for causality on nonsynchronous data. Tests of lead-lag relations between the two markets require stationarity of the time series, a condition achieved only after first-differencing and scaling the original prices to produce time series of rates of return.[4] Formally, let the rates of returns in the two markets be denoted by $X_t = \ln(S_t) - \ln(S_{t-1})$ and $Y_t = \ln(S^*_t) - \ln(S^*_{t-1})$, where $S$ and $S^*$ are the dollar-denominated closing prices quoted in Tel Aviv and New York, respectively. To test whether $X_t$ causes $Y_t$, the rate of return is computed as the percentage change in share prices from Tuesday to Wednesday in both markets ($X_t$ and $Y_t$). However, to test whether $Y_t$ causes $X_t$, the rate of return in Tel Aviv is computed as the price change from Tuesday to Wednesday ($X_t$), and the rate of return in New York as the price change from Monday to Tuesday ($Y_{t-1}$). Nonsynchronous data render impossible any tests of contemporaneous correlations or instantaneous causality.[5]

*Trading Method*

There are a few important differences between the trading methods used on the TASE and NASDAQ. First, the TASE is a batch market where trade is conducted at discrete time intervals; NASDAQ is a continuous dealers market. Second, related to the first difference, orders on the TASE are accumulated and executed together with some delay; buyers and sellers on NASDAQ continuously interact, directly or through dealers. Third, the TASE is an auction market; NASDAQ is a computerized order-driven market—for the most part a dealers market—where the best bid and ask quotes are displayed and used by investors in placing their orders with brokers who execute the orders through dealers or act as dealers for their own account. Fourth, related to the third difference, the TASE operates without bid-ask price quotes; investors on NASDAQ place their orders based on bid-ask quotes, and the execution of those orders usually occurs between the bid and ask prices.

These differences notwithstanding, our decision to base this study on closing daily prices rather than intraday prices was influenced mainly by the unique system of the TASE, which combines two trading mechanisms. The first mechanism is a computerized call market for less liquid stocks. This is a fully automated batch market designed to mimic an auction market where participants on the trading floor react to the difference between aggregated orders to buy

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[4]Most public firms whose shares are listed on the TASE do not pay dividends. Among the five stocks included in our sample, only Teva and Elbit paid cash dividends during the sample period, in both cases generating an average dividend yield below 2 percent. For these stocks, calculated rates of return include the dividend yield.

[5]Open share prices do not exist under the current trading methods on the TASE. Since the data do not allow breaking the analysis into open and close periods, the empirical analysis is limited to close-to-close returns.

(demand) and sell (supply) within given price limits.[6] The second trading mechanism, designed for the 100 most liquid stocks, is a bilateral semicontinuous system. The opening session in the beginning of every trading day, which relies on the first mechanism for the execution of small orders, is completely independent of the second, main session employing the second mechanism. It is apparent that the opening session on the TASE has a different role than that on NASDAQ, since on the TASE the only information revealed to the public before starting the second session is the opening surplus.

Several authors, including Amihud and Mendelson (1987) and George and Hwang (1995), show that a call market may induce an irregular level of volatility at the opening session. This phenomenon is attributed to the different trading methods used in the opening versus mid-day sessions. In view of the different nature of the opening session on the TASE and NASDAQ, and its likely differential effect on price behavior, the use of closing data in our study should improve the accuracy of the estimates.

## IV. Empirical Results

Our preliminary tests of risk and return differences and cointegration across markets are followed below by causality tests using the ARIMA and VAR models.

*Risk and Return*

Table 1 displays descriptive statistics of the sample data based on daily closing share prices over five years beginning July 1988. The standard deviation is based on dollar-denominated rates of return in both markets. The difference in the annual mean rates of return of individual stocks across markets is not significantly different from zero, but the standard deviations are significantly different at the 5 percent confidence level. A comparison of betas and the return volatility explained by the market indices reveals that, in most cases, the proportion of variance explained by the TASE index is significantly greater than that explained by the NASDAQ index. This evidence supports the hypothesis that the price behavior of these stocks in both markets is influenced more strongly by the TASE price index than by the NASDAQ index. Consistent with Garbade and Silber (1979a, b), it also suggests that share prices in the satellite NASDAQ market are more frequently affected by price changes in the domestic TASE market than the other way around.

The greater return volatility of shares traded on NASDAQ deserves further examination. Two possible explanations for this disparity is a greater exposure of

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[6] Of the five stocks included in our sample, only Robotec is traded in the computerized call market.

**TABLE 1. List of Stocks and Descriptive Sample Statistics.**

| | Country | $n$ | Sample Period | Mean | S.D. | ß | $U$ | ß′ | $U'$ |
|---|---|---|---|---|---|---|---|---|---|
| Index | IS | 1316 | 7/88–9/93 | 0.426 | 0.220 | | | | |
| | US | | | 0.101 | 0.126 | | | | |
| | | | | (2.95)** | (3.05)** | | | | |
| Teva | IS | 1316 | 7/88–9/93 | 0.429 | 0.399 | 1.106** | 0.418 | 0.077** | 0.003 |
| | US | | | 0.390 | 0.524 | 0.688** | 0.162 | 1.118** | 0.064 |
| | | | | (0.02) | (1.72)** | | | | |
| Elbit | IS | 1314 | 7/88–9/93 | 0.453 | 0.361 | 1.276** | 0.535 | 0.115 | 0.001 |
| | US | | | 0.436 | 0.401 | 0.877** | 0.253 | 0.649** | 0.021 |
| | | | | (0.01) | (1.23)** | | | | |
| Elron | IS | 1313 | 7/88–9/93 | 0.386 | 0.407 | 1.369** | 0.540 | 0.076 | 0.001 |
| | US | | | 0.346 | 0.545 | 1.022** | 0.301 | 1.086** | 0.051 |
| | | | | (0.01) | (1.79)** | | | | |
| Robotec | IS | 358 | 8/92–11/93 | 0.014 | 0.391 | 0.885** | 0.182 | 0.112 | 0.001 |
| | US | | | 0.000 | 0.596 | 0.369** | 0.032 | 1.301** | 0.052 |
| | | | | (0.00) | (2.32)** | | | | |
| Aryt | IS | 343 | 8/92–11/93 | 0.518 | 0.497 | 1.061** | 0.156 | 0.230 | 0.000 |
| | US | | | 0.507 | 0.689 | 1.180 | 0.194 | -1.117 | 0.023 |
| | | | | (0.00) | (1.94)** | | | | |

Notes: The calculations of the annual mean and standard deviation are based on daily transactions throughout the sample period. β and β′ are estimated as follows:

$$R_{it}(j) = \alpha + \beta R_{mt}(\mathrm{IS}) + \beta' R_{mt}(\mathrm{US}) + e,$$

where $j$ = (IS, US) and where IS stands for Israel and US stands for the United States; $R_{it}$ is the return on stock $i$; $R_{mt}$(IS) and $R_{mt}$(US) are the returns of the TASE general stock index and those of the equally weighted NASDAQ index, respectively; and $U$ and $U'$ are the proportions of a stock's rate of return variance explained by $R_{mt}$(IS) and $R_{mt}$(US), respectively. The correlation between the indices over the five-year sample period, -0.011, is not significantly different from zero. Numbers in parentheses under the mean figures are the $F$-statistics of a one-way analysis of variance testing the hypothesis that the mean stock returns in the two markets are equal. Numbers in parentheses under the standard deviation figures are Pitman statistics for dependent samples testing the hypothesis that the standard deviation of stock returns in the two markets are equal.

**Significant at the 5 percent level.

NASDAQ to the U.S. market factor (see Table 1) and a greater influence of noise traders (Neumark, Tinsley, and Tosini (1991)), possibly due to the underlying trading mechanism.[7] Amihud and Mendelson (1987) argue that the trading

[7]At least theoretically, the return volatility of shares traded on the TASE could be inflated by the volatility of the NIS/$ exchange rate. However, as pointed out above, this would have a negligible effect on our results since the annual standard deviation of daily percentage changes in the exchange rate during the sample period was less than 7 percent, and its correlation to stock returns was close to zero.

**TABLE 2. Cointegration of the Five Dually Listed Stocks.**

| | Direction of Causality | |
|---|---|---|
| Stock | NASDAQ → TASE | TASE → NASDAQ |
| Teva | 1.075 | 1.161 |
| Elbit | 1.114 | 1.138 |
| Elron | 1.056 | 1.219 |
| Robotec | 1.232 | 1.395 |
| Aryt | 1.101 | 1.280 |

Cointegration equation:

$$Y_t = \alpha + \beta X_t + \epsilon_t \qquad (X \rightarrow Y)$$

$$X_t = \alpha + \beta Y_t + \epsilon_t \qquad (Y \rightarrow X)$$

Dickey-Fuller equation:

$$\epsilon_t - \epsilon_{t-1} = -b\epsilon_t + \Phi_t$$

The numbers displayed are the Dickey-Fuller statistics testing the hypothesis $H_0$: $b = 0$. The Dickey-Fuller value at the 5 percent significance level is 3.38. In all cases the null hypothesis of no cointegration is not rejected at the 5 percent level.

mechanism may have a significant effect on stock prices.[8] In particular, they show that the variance of returns of opening prices is greater than that of closing prices, and that the variance increases with illiquidity as measured by the bid-ask spread. Based on Amihud and Mendelson's findings and the fact that the trading volume in the underlying stocks is greater on NASDAQ than on the TASE, the difference in volatility may be affected by the difference in trading mechanisms. Specifically, it may be attributed to the reliance of NASDAQ on market makers that are less efficient in trading less liquid stocks (Hasbrouck (1993)). Trading on NASDAQ is conducted continuously, whereas stocks on the TASE are typically traded three times a day in a predictable order, an arrangement that provides an additional time to accumulate orders and increases transaction liquidity.

*Cointegration*

Table 2 displays the results of the cointegration test. In all cases, prices in the two markets are found not to be cointegrated, indicating that causality tests based on Granger's (1969) definition are well specified. According to Engle and

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[8] See Lauterbach and Ben-Zion (1993) for a description of the trading methods in Israel.

Granger (1987), these results suggest the prices of the stocks were in equilibrium in both markets. In other words, a portion of any price disequilibrium in one period is corrected in the following period.

*ARIMA Causality Tests*

The in-sample and out-of-sample tests under the two methods are based on five partially overlapping samples, each starting in the beginning of July and ending at the close of September the following year. The first twelve months of each sample are the in-sample period, and the following three months are the out-of-sample period.

Using the ARIMA models, we generate post-sample, one-step-ahead forecasts from July–June for the following July–September of each year and compute the resulting forecasting errors. This allows testing for robustness of out-of-sample performance. Because of the similarity of our results for the five periods, we report results for only two periods in Tables 3, 4, and 5.[9] The first in-sample period is July 1990–June 1991, followed by the post-sample period July–September 1991. The second in-sample period is July 1992–June 1993, followed by the post-sample period July–September 1993.

Table 3 reports the results of the first step of the procedure outlined in section II where a univariate model is identified and diagnostically checked for each stock. In all cases, the residual time series show no significant serial correlation after first-differencing the original figures with a second-order to fourth-order autoregressive (AR) process and a first-order to second-order moving-average (MA) process. The transformation of the data to rates of return is essential for achieving stationarity.

Table 4 contains the results of the second step of the ARIMA procedure in which cross-correlograms $r_k$ of the appropriate pairs of residual series are computed for $k$ lags between -5 and +5. The null hypothesis is that $r_k$ is not significantly different from zero. Assuming these correlations are normally distributed around zero, for moderate and large lags the standard deviation of $r_k$ is approximately $1/\sqrt{N}$ where $N$ is the number of residuals. In this study, $r_k$ is considered significantly different from zero if it falls outside the interval $[-2\sqrt{N}, +2\sqrt{N}]$. In general, significantly positive cross-correlograms are found for $k = -1, +1, +2$, and in some cases for $k = +3$ (Elbit and Teva). These results, which characterize all five stocks in all periods, imply that price changes in New York are strongly affected by price changes in Israel that occurred earlier the same day. The opposite effect is considerably weaker. In contrast, the significant cross-correlograms between the

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[9]Qualitatively similar results were obtained when the five-year sample period was divided into two periods of various lengths, using the first as an in-sample period.

**TABLE 3. Univariate ARIMA Models Using the Box-Jenkins Procedure.**

| Stock | | Period[a] | AR(1) | AR(2) | AR(3) | AR(4) | MA(1) | MA(2) | $\chi^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Index[b] | IS | I | -0.819** | | | | -0.919** | -0.195** | 13.6 |
| | US | | -0.551** | 0.329** | | | -0.847** | | 11.2 |
| | IS | II | -0.109** | -0.839** | | | -0.121 | -0.738** | 8.0 |
| | US | | 0.162** | | | | | | 19.1 |
| Teva | IS | I | 0.394** | 0.687** | -0.165** | | 0.379** | 0.607** | 7.6 |
| | US | | -1.660** | -0.986** | -0.118** | | -1.655** | -0.874** | 9.0 |
| | IS | II | 1.272** | -0.947** | | | 1.246** | -0.970** | 6.0 |
| | US | | -1.317** | -0.705** | | | -1.379** | -0.839** | 7.4 |
| Elbit | IS | I | 0.467** | 0.635** | -0.170** | | 0.408** | 0.546** | 8.4 |
| | US | | -1.339** | -0.975** | -0.011** | | -1.357** | -0.994** | 8.7 |
| | IS | II | -1.115** | -0.292 | 0.089 | 0.138** | -1.157** | -0.369 | 6.2 |
| | US | | -0.855** | | | | -0.883** | | 3.4 |
| Elron | IS | I | -0.546** | 0.198** | | | -0.627 | | 10.2 |
| | US | | -0.137** | -0.099** | | | | | 4.7 |
| | IS | II | 0.046 | 0.100** | | | | | 17.0 |
| | US | | -0.066 | 0.012** | | | | | 9.1 |
| Robotec | IS | II | 0.370** | 0.540** | | | 0.358** | 0.640** | 10.0 |
| | US | | 0.458** | -0.530** | -0.119 | 0.115** | 0.726** | -0.638** | 12.6 |
| Aryt | IS | II | -0.320** | -0.754** | -0.403** | | -0.885** | | 7.6 |
| | US | | -0.235** | | | | | | 11.7 |

$$R_t - \phi_1 R_{t-1} - \ldots - \phi_p R_{t-p} = e_t - \Theta_1 e_{t-1} - \ldots - \Theta_q e_{t-q}$$

This is an autoregressive-moving average model, ARMA($p,q$), where the integers $p$ and $q$ stand for the order of the autoregressive term, AR($p$), and the moving average term, MA($q$), respectively. The parameters $\phi_1, \phi_2, \ldots, \phi_p$ and $\Theta_1, \Theta_2, \ldots, \Theta_q$ are subject to some restrictions (Box and Jenkins (1970)) to ensure stationarity. $R_t = \ln(P_t) - \ln(p_{t-1})$, where $P_t$ is the share price at time $t$. This representation of the ARIMA models assumes that stationarity of the time series of stock returns is achieved after first-differencing. $e_{t-q}$ is the shock that enters the system during previous periods. The test for the adequacy of the time series model is $\chi^2 = N \Sigma_{k=1,L} r^2_k(e)$, where $r_k$ is a residual autocorrelation of lag $k$, $\chi^2$ is distributed chi-square with $L-k$ degrees of freedom, $L$ is the number of residual correlations (twelve in this test), and $N$ is the number of residuals. A too-large value of $\chi^2$ is evidence against model adequacy.

[a]Period I is 7/90–6/91 for the in-sample and 7/91–10/91 for the out-of-sample. Period II is 7/92–6/93 for the in-sample and 7/93–10/93 for the out-of-sample.
[b]The indices are the equally weighted NASDAQ index in New York and the TASE general stock index in Tel Aviv.

**Significant at the 5 percent level.

NASDAQ and TASE price indices indicate no general causal effect of stock prices in Israel on those in the United States. The significant causality in the opposite direction is consistent with the strong economic ties between the two countries, which are dominated by the larger U.S. economy.

**TABLE 4. Cross-correlograms for Residual Series.**

| | | Correlation for lag $k$ (in percentages) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock | Period[a] | -5 | -4 | -3 | -2 | -1 | +1 | +2 | +3 | +4 | +5 |
| Index[b] | I | -0.61 | 1.50 | 11.1 | 6.88 | 21.6** | 2.90 | -0.83 | 9.63 | -9.47 | -12.1 |
| | II | 10.2 | 2.50 | 5.20 | 12.8** | 22.5** | 1.91 | -2.89 | -5.73 | 0.68 | 3.09 |
| Teva | I | 2.79 | 3.80 | 0.30 | -1.13 | 16.7** | 25.7** | 17.9** | 11.9 | -2.01 | -0.42 |
| | II | 3.41 | 5.83 | 9.82 | 5.69 | 34.6** | 29.2** | 4.78 | -1.60 | -1.47 | 0.39 |
| Elbit | I | 0.40 | 14.0 | 2.19 | 6.83 | 16.1** | 30.3** | 17.9** | 13.7** | -3.11 | 0.36 |
| | II | 6.37 | -2.62 | 2.31 | -7.00 | 21.3** | 55.5** | 17.4** | 3.22 | 1.55 | 3.23 |
| Elron | I | 2.41 | 3.59 | -0.50 | 3.60 | 16.6** | 31.7** | 26.3** | 4.49 | 3.74 | 7.60 |
| | II | 2.28 | 3.64 | 1.19 | 5.01 | 19.3** | 52.7** | 18.8 | -2.33 | -4.88 | 2.76 |
| Robotec | II | 4.49 | 1.81 | 8.37 | 3.26 | 23.0** | 26.0** | 23.8** | 6.33 | -3.21 | -1.59 |
| Aryt | II | 0.11 | -3.02 | 0.67 | 6.38 | 15.5** | 28.3** | 29.7** | 10.4 | -8.09 | -6.69 |

Notes: Cross-correlograms are computed between the residuals for $k$ lags of the two time series models. The first model is for stock prices in Tel Aviv ($X_t$), and the second is for stock prices in New York ($Y_t$). Correlations between residuals are computed by $r_k = \text{corr}(\epsilon_{x_t}, \epsilon_{y_{t+k}})$. We report the cross-correlograms between the time series residuals only up to the fifth lead and lag since no correlogram was significant for higher leads and lags. We disregard significant correlations when surrounded by very low correlations. When $r_k$ is significantly different from zero for $k > 0$, it tentatively indicates that $X$ causes $Y$. When $r_k$ is significantly different from zero for $k < 0$, it tentatively indicates that $Y$ causes $X$. $r_k$ is significantly different from zero at the 5 percent level if it falls outside the interval

$$[-2/\sqrt{N}, +2/\sqrt{N}] = [-12.6 \text{ percent}, +12.6 \text{ percent}]$$

where $N$ is the number of residuals. Here, $N = 250$, representing the number of trading days for the in-samples in each period. Note that because of differences in the trading time between the two markets, contemporaneous correlations do not exist.

[a]Period I is 7/90–6/91 for the in-sample and 7/91–10/91 for the out-of-sample. Period II is 7/92–6/93 for the in-sample and 7/93–10/93 for the out-of-sample.
[b]The indices are the equally weighted NASDAQ index in New York and the TASE general stock index in Tel Aviv.

**$r_k$ is significantly different from zero at the 5 percent level.

To identify the relations between the residuals of the univariate models, we generate forecasting errors with the univariate and bivariate models following steps 3, 4, and 5 of the ARIMA procedure.[10] The results displayed in Table 5 suggest significant, unidirectional causality between the prices of stocks traded in the two

[10]Sims (1980) criticizes causality tests that are based only on correlations between estimated residuals because such correlations tend to bias bivariate models. Those correlations are nevertheless useful for tentative identification of such models.

**TABLE 5. Causality Between the Prices of Dually Listed Stocks Based on In-Sample and Out-of-Sample Data Using the ARIMA Model.**

| | | $X \to Y$ MSE(X)/MSE(X,Y) | | $Y \to X$ MSE(Y)/MSE(Y,X) | |
|---|---|---|---|---|---|
| | Period | In-Sample | Out-of-Sample | In-Sample | Out-of-Sample |
| Index[b] | I | 1.057 | 0.928 | 1.093*** | 0.970 |
| | II | 1.007 | 0.888 | 1.112*** | 0.784 |
| Teva | I | 1.190*** | 1.469*** | 1.038* | 1.082*** |
| | II | 1.122*** | 1.074 | 1.178*** | 1.288*** |
| Elbit | I | 1.222*** | 1.299*** | 1.037* | 1.031 |
| | II | 1.754*** | 1.644*** | 1.094*** | 1.069 |
| Elron | I | 1.284*** | 2.432*** | 1.036* | 1.001 |
| | II | 1.690*** | 1.759*** | 1.066** | 1.048 |
| Robotec | II | 1.254*** | 1.420*** | 1.066** | 1.011 |
| Aryt | II | 1.107*** | 2.582*** | 1.011 | 0.996 |

Notes: $X$ and $Y$ are the rates of return on shares listed on the TASE and NASDAQ, respectively. MSE($X$) is the mean-squared errors of the univariate model, and MSE($X,Y$) is the mean-squared errors of the bivariate model. "In-sample" and "out-of-sample" denote the ratio of the mean-squared errors of the univariate model to that of the bivariate model for the in-sample and out-of-sample data. Following Ashley, Granger, and Schmalensee (1980), the test calls for estimating the simple regression $\delta_t = \alpha_0 + \alpha_1[\Sigma_t - \mu(\Sigma_t)] + \Omega_t$, where $\delta_t = \epsilon_{1t} - \epsilon_{2t}$ and $\Sigma_t = \epsilon_{1t} + \epsilon_{2t}$; and $\epsilon_1$ and $\epsilon_2$ are the forecasting errors of the univariate and bivariate models, respectively. If $\alpha_0 = \alpha_1 = 0$, the null hypothesis of no causality cannot be rejected against the alternative hypothesis of causality where both $\alpha_0$ and $\alpha_1$ are nonnegative and at least one of the two parameters is positive.

[a]Period I is 7/90–6/91 for the in-sample and 7/91–10/91 for the out-of-sample. Period II is 7/92–6/93 for the in-sample and 7/93–10/93 for the out-of-sample.
[b]The indices are the equally weighted NASDAQ index in New York and the TASE general stock index in Tel Aviv.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

markets. In all cases, price changes on the TASE cause similar price changes for the same stocks on NASDAQ. The in-sample MSEs of the bivariate model are significantly smaller than those of the univariate model, ranging from 11 percent for Aryt to over 75 percent for Elbit. Significant causality is also revealed in examining the post-sample data. Reversed causality is weaker and present only for the in-sample data.

In our overall interpretation of the results, we follow Ashley, Granger, and Schmalensee (1980), who argue that causality tests should rely more heavily on out-of-sample data since model specifications may be infected by sampling errors that bias in-sample tests. Based on out-of-sample results for the five stocks studied, we conclude that price changes on the TASE cause price changes on NASDAQ, but not the other way around. Based on out-of-sample data, we further conclude that causality is absent between the NASDAQ and TASE general price indices.[11]

*VAR Causality Tests*

Next, we seek to determine the robustness of the above empirical findings using the VAR model. Unlike the ARIMA model, the predictive power of the VAR model in the out-of-sample test is based on the computed response of a pre-identified system of equations (representing the statistical relations between the time series) to an innovation assuming the form of an initial random shock. Following Sims (1980), we measure the extent of innovation (i.e., the influence of each variable) by decomposing the variance of forecasting errors according to the contribution of each variable.

Table 6 shows the percentage of forecast-error variance for a *k*-day forecast generated by an innovation in each market in the two periods. Panel A displays responses to price innovations on NASDAQ, and Panel B displays responses to innovations on the TASE. Absent a formal test of significance, a response is considered insignificant if most of the variance of errors is explained by a market's own past stock price behavior. The results confirm that this is largely the case for the five stocks in both markets, but especially for those traded on NASDAQ. For example, after five trading days the price response of Teva traded on NASDAQ to its own innovation in the first period accounts for about 92 percent of the variance of errors; the parallel figure for the TASE is 87 percent.[12] These results indicate weak causality from the TASE to NASDAQ and still weaker reversed causality. The results for Elron and Elbit are similar, but those for Aryt and Robotec show no causality across markets in either direction.

*Comparing the Models*

A comparison between the two models reveals that results based on the VAR model are qualitatively similar but quantitatively poorer than those based on the ARIMA model, where some causality is shown in both directions. These differences reflect differences in the models themselves. Lupolleti and Webb (1986)

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[11]This test was repeated to investigate a possible day-of-the-week effect. The revised test was based on subsamples that included only transactions executed during weekdays, excluding weekends and holidays. We found generally stronger causality during weekdays, but the results were qualitatively similar: the relations for in-sample tests were more significant than those for out-of-sample tests. The only difference was for Elbit and Elron in the second period, which showed significant causality from New York to Tel Aviv.

[12]This means that only 8 percent of the return variance of shares traded on the TASE is explained by price changes on NASDAQ, compared with 13 percent of the return variance of shares traded on NASDAQ explained by price changes on the TASE.

**TABLE 6. Out-of-Sample Test Using a Bivariate VAR Model: Decomposition of Forecasting Errors.**

| Period | Forecasting Step Ahead (Days) | Teva | Elbit | Elron | Robotec | Aryt |
|---|---|---|---|---|---|---|
| Panel A. Price Innovation on NASDAQ | | | | | | |
| 7/90–6/91 | 1 | 100.00 | 100.00 | 100.00 | | |
| | 2 | 99.67 | 99.88 | 99.99 | | |
| | 3 | 94.15 | 97.05 | 91.11 | | |
| | 5 | 91.94 | 96.57 | 88.53 | | |
| 7/92–6/93 | 1 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| | 2 | 99.87 | 97.96 | 99.93 | 99.99 | 98.75 |
| | 3 | 99.88 | 97.82 | 99.13 | 99.47 | 95.17 |
| | 5 | 99.83 | 97.68 | 99.14 | 99.47 | 94.21 |
| Panel B Price Innovation on the TASE | | | | | | |
| 7/90–6/91 | 1 | 100.00 | 100.00 | 100.00 | | |
| | 2 | 88.44 | 92.78 | 83.24 | | |
| | 3 | 85.41 | 84.00 | 82.40 | | |
| | 5 | 85.23 | 81.23 | 80.13 | | |
| 7/92–6/93 | 1 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| | 2 | 96.95 | 91.80 | 83.24 | 95.82 | 99.69 |
| | 3 | 96.71 | 90.72 | 82.40 | 95.86 | 99.08 |
| | 5 | 97.34 | 90.37 | 80.13 | 95.80 | 98.95 |

Notes: Reported is the percentage of forecasting errors variance attributed to stock price movements in the same market ($R_{t-j}$), as opposed to price movements of the same stock in the other market, based on a forecast $k$ days ahead and an initial price shock (innovation) equal in size to one standard deviation of the rate of return of that stock.

argue that although both models are useful for making predictions, they go about it in different ways. The ARIMA model is advantageous in predicting share prices with a limited preconception of the underlying structure. In contrast, the VAR model is designed to test for a price response with a pre-identified system of equations. Our superior out-of-sample forecasts using the ARIMA model strongly suggest that price changes on the TASE lead price changes on NASDAQ.

Despite differences in detail, the results of the two models are largely consistent in the context of this study. Our primary objective in supplementing the ARIMA tests by those of the VAR is to assess robustness. Like Ashley, Granger, and Schmalensee (1980), we look at the results of both models in determining the nature of causality. Out-of-sample tests with the ARIMA model show that price changes on the TASE cause price changes on NASDAQ, and, except for Teva, reversed causality does not exist. The VAR model shows poorer forecasts of stock price changes in both directions, but still a greater influence from the TASE to NASDAQ for all five stocks (Table 6, Panel B). Furthermore, based on in-sample tests, under both models we find for all stocks significant causality between price changes in each market and price changes with a time lag in the other market. Broadly speaking, these results confirm the findings of Chowdhry and Nanda (1991) that stock price changes in the home market have a stronger influence on prices in the satellite market than the other way around.

## V. Summary

We examine the linkage between the prices of stocks listed in more than one market. The data are from five companies based in Israel whose stocks are traded on the TASE and NASDAQ. This linkage is investigated for Granger-type causality using the ARIMA and VAR models from which forecasting errors of stock returns are estimated for the causality tests. Results based on in-sample data reveal causality and reverse causality between prices in the two markets. However, results based on out-of-sample data show a weak unidirectional causality from the TASE to NASDAQ. This asymmetry suggests the domestic market plays a dominant role relative to the foreign market. An additional finding is that mean stock returns are not significantly different in the two markets, but volatility is significantly greater on NASDAQ.

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