Stock Market's Response to Real Output Shocks in Eastern European Frontier Markets: A VARwAL / VECwAL Model

ABSTRACT

We study stock market's response to real output shocks in the small and young Eastern European frontier markets, and compare it to that in the larger European emerging markets and world's most developed markets. To obtain a complete time profile of stock market's response, we use a Vector Auto-regression with Asymmetric Leads (VARwAL) model, which we also extend into a Vector Error-Correction with Asymmetric Leads (VECwAL) model. A comparison across countries based on VARwAL/VECwAL impulse-responses enables us to assess the impact of market development on the stock market's response to macroeconomic activity shocks. Results confirm the efficacy of the VARwAL/VECwAL model: in every country, the delayed response is significant. Stock market returns forecast future real output equally well in Eastern European frontier markets as in developed and larger-emerging markets. However, a large part of this forward-looking ability seems to be driven by structural reforms, whereas the near-horizon forward-looking ability in developed-emerging markets seems to be driven by information.

JEL classification: E44, P34, G14, C58

Keywords: stock market – real output linkage, Eastern European frontier markets, VARwAL/VECwAL model

1. Introduction

An extensive literature has accumulated on the interaction between the stock market and macroeconomic activity in developed and emerging markets following Fama's (1990) seminal work: for example, Lee (1992), Gallinger (1994), Choi et al. (1999), Binswanger (2000, 2004), Shanken and Weinstein (2006), Laopodis (2011) on developed markets; Rangvid (2001), Mauro (2003), Tsouma (2009) on emerging markets. Major Central and Eastern European (CEE) emerging markets have been covered within this literature (e.g., Hanousek and Filer, 2000; Lyocsa et al., 2011). However, a comprehensive study of the young frontier stock markets in Eastern Europe is currently a gap. These young stock markets and transition economies offer an opportunity to investigate the effect of market development on stock market's ability to forecast future macroeconomic activity.

The current paper fills this gap by studying the time profile of stock market's response to real output shocks in the small and young frontier markets Bulgaria, Croatia, Estonia, Latvia, Lithuania, Romania, Slovenia and Ukraine. We compare these results to those from the larger European emerging markets, Czech Republic, Hungary, Poland, Russia and Turkey, as well as world's most developed markets, Germany, Japan and US. These comparisons will enable us to add to the literature that investigates the role of market development in shaping the stock market – real economy connection (see, for example, Mauro, 2003).

The second contribution of this paper is to employ the Vector Auto-regression with Asymmetric Leads (VARwAL) model in order to obtain a complete time-profile of stock market's response to real output news. We also extend the VARwAL model, contemporaneously introduced by Ülkü and Kuruppuarachchi (2015), to incorporate a long-run cointegrating vector where necessary, which forms the Vector Error Correction with Asymmetric Leads (VECwAL) model. VARWAL and VECwAL models are particularly needed when the purpose is to assess stock market's forward-looking function, and to compare it across countries to find whether lack of market development is associated with an absence of such function.

The efficacy of the VARwAL and VECwAL models follows from a void in this line of literature: In his seminal work, Fama (1990) documents the forward-looking behavior of the stock market via a regression of current stock market returns on future output growth, and a regression of current output growth on past stock market returns. However, Fama's regressions portray only the forward-looking part of the stock market's response to real output news; they do not allow a lagged reaction. Subsequent to Fama's single equation approach, time series techniques have become widespread to capture the dynamic interaction and potential long-run relationships between stock market indexes and real output; examples include Choi et al. (1999), Binswanger (2004), Laopodis (2011). However, these Vector Auto-regression (VAR) or Vector Error Correction (VEC) models unnecessarily divide stock market's response to real output news into two opposite implied directions of causality based on the sequence of time. The interaction between stock market and real output a special case, where time-order does not necessarily justify a switch in the direction of causality, as further discussed below. Moreover, these standard approaches do not permit combining the two artificially-divided parts of stock market's market response. Thus, they do not enable researchers to obtain a complete time profile of stock market's response.

Puzzling inconsistent findings have lead to a debate about whether the stock market is sufficiently connected to the real economy (see Domian and Louton, 1997; Canova and De Nicolo, 1995; Binswanger, 2000, 2004; Flannery and Protopapadakis, 2002; Shanken and Weinstein, 2006; Du et al., 2012). Potential explanations for the (alleged) lack of a strong connection include irrational stock market bubbles (Binswanger, 2000, 2004) and measurement noise in macroeconomic activity and output statistics (Du et al., 2012). Since these explanations have important implications on market efficiency, rational behavior of market participants and the efficacy of macroeconomic statistics, it is crucial, before reaching such conclusions, to employ the most informative methodology to obtain a complete time profile of stock market's response to real output news.

The interaction between the stock markets and macroeconomic activity requires special treatment due to the forward-looking nature of the stock market (i.e., rational expectations along with a strong incentive to predict the future): 'effect' precedes the cause', i.e., stock market leads macroeconomic activity. However, stock markets may also display a lagged response to output news as information-processing capabilities of market participants are not perfect. In order to obtain a complete picture of the stock market - real output linkage, the forward-looking and lagged responses of the stock market need to be combined. VAR and VEC models capture the forward-looking and lagged responses of the stock market in two different equations, but do not combine them. Moreover, the switch between equations unjustifiably implies a switch in the direction of causality. A complete time profile has surprisingly not been obtained in previous studies. Our VARwAL/VECwAL models, presented in Sections 2.1 and 2.2, obtain a complete trajectory of the stock market's response by adding lead terms to an otherwise standard structural VAR/VEC model. Furthermore, they enable us to construct an indicator stock market's forward-lookingness, which can be considered as a measure of market efficiency. These tools enable an informative assessment of the effect of market development on stock market's forward-looking characteristics.

The results, depicted in Section 3, confirm the efficacy of the VARwAL/VECwAL models: the delayed response of the stock market, ignored in Fama (1990) regressions, turn out to be significant in every country in our sample. The overall response pattern is quite similar across European frontier, European emerging and world developed markets. However, several differences are notable: First, the magnitude of the total cumulative response, measured in stock market return standard deviations, to a 1-standard deviation real output shock is considerably larger in frontier markets. Second, a larger proportion of the forward-looking response comes in distant-leads (near-leads) in frontier (developed) markets. Distant-lead forward-looking behavior of the stock market can be attributed to structural changes that cause covariation in both stock market returns and economic growth (e.g., opening up domestic capital markets to foreign investors, EU accession, structural reforms) while near-lead forward-looking behavior can be attributed to informational efficiency. Thus, the distant-lead forward-looking behavior of Eastern European frontier stock markets should not be interpreted as evidence of stronger informational efficiency. Yet, the overall time profile of stock market response suggests that Eastern European frontier markets are no worse than developed and emerging markets. Section 4 concludes by outlining these findings along with interpretations.

2. Methodology and Data

We focus on a bi-variate case between log real stock index (S_t) and log real industrial production index (IP_t), and employ monthly data.[1]

2.1. Issues resulting from the use of standard time series techniques in studying stock market – real output interaction

First, the use of cointegration tests in this context leads to results that are sensitive to persistent changes in expected returns (see Timmerman, 1995).[2] As expected returns are unobservable, interpreting absence of

[1] In this setting, there is no need to separately handle cross-country effects, because cross-country interdependence (i.e., the relevant portion of other countries' output news) will be reflected in the production index of the country under study, and we will be assessing whether a country's stock market rationally responds to its own real output news regardless of its source. Extant evidence suggests a close connection between a country's stock market world beta and real output world beta, implying that stock markets rationally incorporate information on global macroeconomic interdependence (Ülkü and Baker, 2013).

cointegration between real output and stock market index is difficult. Not surprisingly, studies employing cointegration tests portray a picture of conflicting results. To cite a few examples: Mukherjee and Naka (1995), Choi et al. (1999), Nasseh and Strauss (2000) find significant cointegration between real output and stock market levels, while Cheung and Ng (1998), Hassapis and Kalyvitis (2002) and Laopodis (2006, 2011) fail to obtain reliable cointegrating relationships. Conflicting results across countries and subperiods may be due to persistent changes in expected returns and/or changes in the country's macroeconomic and market structure (e.g., the rise of the 'new economy' and global outsourcing in the US, which renders conventional industrial production statistics less relevant for the valuation of US firms). The problem is further exacerbated in studies on frontier markets due to short sample periods and significant structural changes in the economy and stock market (e.g., base-broadening following opening up the local markets to foreign investors; Henry, 2000).

Second, S_t and IP_t may not exhibit common stochastic trends; but this does not necessarily mean that the stock market is disconnected from the real economy: they may vary in common cycles (see Morley and Pentecost, 2000, for a related illustration). Therefore, cointegration test results are an insufficient measure of the stock market – real output interaction. The long-run cointegrating relationship, if significant, only adds an error correction (EC) term to a VAR model. An important part of the interaction is captured by the dynamic (short-term) components. Therefore VAR models should be considered as the baseline specification. Then, it is straightforward to add an EC term (i.e., switch to a VEC model) if a significant cointegrating vector exists.

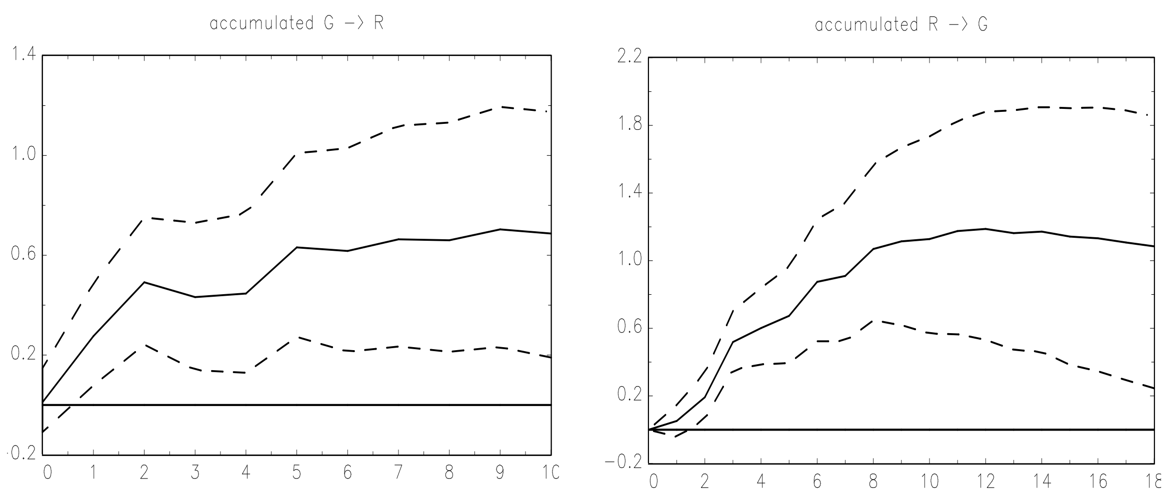
While VAR/VEC models are the most appropriate in this context, a subtle problem seems to have so far escaped attention in the literature: VAR and VEC models show the association between past output and current stock market returns and that between current output and past returns in two equations. They do not offer a means of combining the parts, and do not enable to obtain the full time profile of stock market's response.

This problem is illustrated in Figure 1 below. Consider a bivariate VAR model with G_t and R_t, where $G_t = IP_t - IP_{t-1}$ is the real output growth rate and $R_t = S_t - S_{t-1}$ is stock market real return. Stock market's lagged response to output news can directly be observed from the $G_t \rightarrow R_t$ impulse-response, and its forward-looking response can be inferred from the $R_t \rightarrow G_t$ impulse-response. Figure 1 depicts the results on US, as a baseline case, for the 2000-2015 sample period. In the upper row, where the results from a standard VAR model with 10

[2] Recall that the theoretical connection between the stock index and real output results from the present value model: $P_0 = \sum_{t=1}^{\infty} \frac{E_0(CF_t)}{(1+r)^t}$ where P_0 is the current stock index, $E_0(CF_t)$ is the current expectation of future cash flows to firms and r is the expected (or required) return. Timmerman (1995) shows that persistent changes in r can be responsible for empirical failure to detect a cointegrating relationship between stock index and real output, as a proxy for aggregate cash flows.

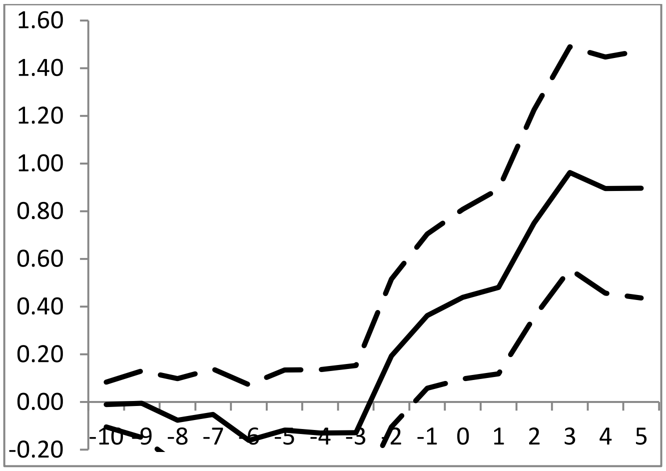
lags[3] are depicted, the $G_t \rightarrow R_t$ impulse-response (on the left) suggests that the stock market exhibits a significantly positive delayed reaction to an industrial production shock in month 0. The $R_t \rightarrow G_t$ impulse-response (on the right) indicates, under the standard interpretation, highly significant responses of the industrial production to a return shock in month 0. In reality, at least a large part of it it should be interpreted as an indication of stock market's significant forward-looking response to future industrial production growth; however, the fact that the impulse-response simulates real output's behavior following a stock market return shock complicates the interpretation. Standard VAR divides stock market's response into two components of opposite implied direction of causality and does not offer a means of combining them. Our VARwAL/VECwAL model result in the lower row provides an accurate description of the phenomenon and a complete time profile of stock market's response to an industrial production shock that will occur in month 0. Note that the industrial production data for month 0 is announced in US around the middle of month 1. Thus, the cumulative response by month 0 can be regarded as 'forward-looking', while the response from month 1 can be regarded as 'delayed'. Fama's (1990) regressions ignore the latter part, as elaborated on by Ülkü and Kuruppuarachchi (2015). Our results show that both parts are significant, indicating the efficacy of our VARwAL/VECwAL models.

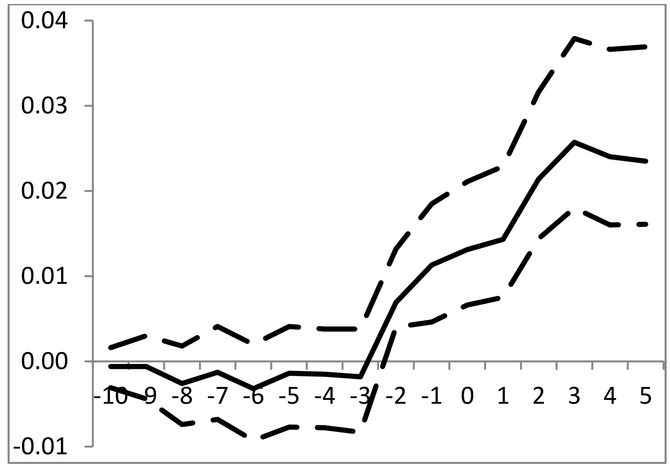
Figure 1. A comparison of standard VAR, VARwAL and VECwAL results



[3] The estimated VAR system is: $G_t = \omega_1 + \sum_{i=-10}^{-1} \psi_i G_{t+i} + \sum_{j=-10}^{-1} \theta_j R_{t+j} + \varepsilon_{1,t}$

$$R_t = \omega_2 + \sum_{i=-10}^{-1} \gamma_i G_{t+i} + \sum_{j=-10}^{-1} \lambda_j R_{t+j} + \varepsilon_{2,t}$$





Notes: The upper row depicts the impulse-response of *R* to a shock in *G* (on the left) and the impulse-response of G to a shock in *R* (on the right), both obtained from a standard VAR model shown in footnote 3. The lower row depicts the impulse-response of *R* to a shock in *G* that occurs in month 0 obtained from our VARwAL model (on the left) and from our VECwAL model (on the right), both described below. Note that the scale of the VECwAL impulse-response is not comparable since the series are not standardized.

The nature of the stock market - output linkage is different from a standard VAR/VEC setting in that a cause (output) can influence not only the contemporaneous and future but also past values of an effect (stock market). Standard econometric theory (e.g., Granger-causality) is based on an interpretation of sequence of time: "cause must precede effect". This construct does not apply to the stock market - output linkage. As stock market participants are strongly incentivized to predict the future, and production is the final outcome of a long process, effect typically precedes cause.[4] This feature is well-captured in Fama (1990) regressions.

Alternating the direction of causality would amount to switching from the "passive informant" hypothesis of Morck et al. (1990) to alternative hypotheses where stock market may act as a "sun spot" influencing macroeconomic activity. Morck et al. (1990) present evidence that, when fundamental factors that drive business investment are properly controlled for, stock returns' incremental power to explain future investments is quite small. The role of equity markets in European economies is much more dismal compared to the US where equity investing is a culture. In Europe, listed equity holdings constitute a much smaller share of household wealth and aggregate financing (e.g., Köke and Schröder, 2002). In the frontier markets analyzed in the current study, the role of equity markets in driving investments and consumption is even much more limited.

Furthermore, we measure stock market's response to output shocks over a relatively short time window which excludes wealth effects on consumption and q-theory effects on investment that have been shown to operate over longer time horizons (see Poterba, 2000 and Funke, 2004 on the former; Barro, 1990 and Morck et

[4] Of course, an actual causality from the stock market to the real output may operate due to wealth effects on consumption, q-theory effects on business investment and shorter-run confidence effects. The discussion on this direction of causality is controversial as some authors claim that the stock market *caused* the 2008 recession (Farmer, 2012); but it is difficult to econometrically differentiate between *causing* and *preceding*. Yet, most of the literature specifically investigating the aforementioned channels of causality from the stock market to real output find that such effects are modest over the horizon focused on in the current study. Below, we discuss this issue in detail.

al., 1990 on the latter). Perhaps, the only assumption we have to make in our empirical model is the exclusion of sentiment effects of the stock market on the economy. Once again, as the role of the stock market in these frontier economies is minor, sentiment effects should also be reasonably slim. Therefore, there are valid reasons for adapting the passive informant assumption in this study. For the same reasons, switching the implied direction of causality based on a time order is strictly counter-intuitive.

2.2. A new solution: the VARwAL and VECwAL models

The VARwAL model, concurrently presented in Ülkü and Kuruppuarachchi (2015), adds the leads of real output growth in the stock market return equation within a bivariate VAR system, in line with the principle of keeping the cause and effect consistently on the same side of the equation.

$$G_t = \omega_1 + \sum_{i=l}^{-1} \psi_i G_{t+i} + \sum_{j=l-f-1}^{l-1} \theta_j R_{t+j} + \varepsilon_{1,t}$$

$$R_t = \omega_2 + \sum_{i=-f}^{-l} \gamma_i G_{t+i} + \sum_{j=-f}^{-1} \lambda_j R_{t+j} + \varepsilon_{2,t} \qquad (1)$$

where i is an index of months from lag l to lead f. In the current study, a 15-month time-window, over which stock market's reaction to an IP innovation in month 0 is monitored, is constructed by setting $l = -10$ and $f = +4$.[5] This window covers the forward-looking part, and it also allows a delayed response by the stock market. Thus, unlike the perfect foresight assumption implicit in Fama (1990), we allow market participants to complete their response after observing macroeconomic activity. Such a specification is particularly needed to identify potential laggard responses, when the aim of the study is to investigate the impact of market development on stock market's forward-looking information content.

In the current paper, we extend the VARwAL model by allowing an error correction (EC) term within a VEC framework. This leads to a VECwAL model, as follows:

$$G_t = \omega_1 + \sum_{i=l}^{-1} \psi_i G_{t+i} + \sum_{j=l-f-1}^{l-1} \theta_j R_{t+j} + \alpha_1 EC_{t-1} + \varepsilon_{1,t}$$

$$R_t = \omega_2 + \sum_{i=-f}^{-l} \gamma_i G_{t+i} + \sum_{j=-f}^{-1} \lambda_j R_{t+j} + \alpha_2 EC_{t-1} + \varepsilon_{2,t} \qquad (2)$$

As in a standard VEC approach, the EC term contains the cointegrating vector set equal to zero, i.e., $EC_t = S_t - \beta \cdot \mathrm{E}(IP_{t+l}) = 0$. Note that in our specification, the cointegrating vector is established, in line with the underlying present value model, between current stock market and expected future output, for which IP_{t+l} is used as a proxy. The procedure requires first a Johansen cointegration test between IP and S. When no cointegrating relationship is found, the model in Eq.(2) collapses to the VARwAL model in (1). Thus, the VARwAL model introduced by

[5] Beyond months t–10 and t+4, the responses are statistically insignificant and usually inconsistently signed (i.e., positive coefficients adjacent to negative coefficients) with large standard errors.

Ülkü and Kuruppuarachchi (2015) is a special case of the VECwAL model in Eq.(2). If a cointegrating vector is found, the EC term shown in Eq.(2) is added.[6]

In Appendix A, we show that this model yields a consistent and efficient estimator. Adding asymmetric lead terms to a VAR/VEC model is new to the literature, however under the assumption of weak exogeneity of *IP*, this becomes a relatively straightforward extension. For the reasons explained above, the role of the stock market in influencing real output is dismal in European frontier markets, which justifies the assumption.

2.3. Data

Our proxy for real output is industrial production, which is available at the monthly frequency and displays more cyclical variation which better reflects macroeconomic fluctuations than GDP. Real industrial production growth rate data adjusted for seasonality and calendar effects (*IP*) are from OECD and UNECE (for non-OECD countries). Stock market data come from MSCI country indexes (where available) or national stock indexes in local currency. Stock returns are adjusted for inflation (CPI growth rate). Our sample period spans from January 2000 to June 2015.[7] Summary statistics and variable diagnostics are presented in Table 1. Further variable diagnostics are available in the online appendix.

Table 1. Summary statistics

	G (in percentage points)			*R*		
Country	mean	st.dev.	ADF*	mean	st.dev.	ADF*
Bulgaria	0.248	2.615	-15.85	0.000	0.098	-4.51
Croatia	0.118	2.777	-10.42	-0.003	0.069	-10.47
Estonia	0.460	2.834	-2.78	0.007	0.076	-10.55
Latvia	0.333	2.108	-4.99	0.004	0.068	-10.33
Lithuania	0.509	5.413	-10.49	0.006	0.073	-8.78
Romania	0.316	2.032	-17.99	0.005	0.097	-10.17
Slovenia	0.176	2.264	-14.79	0.000	0.056	-4.26
Ukraine	0.136	2.416	-9.77	0.004	0.122	-8.08
Czech R.	0.327	1.628	-4.11	0.003	0.066	-12.45
Hungary	0.376	2.623	-17.13	-0.003	0.080	-6.00
Poland	0.451	1.852	-18.38	-0.002	0.070	-12.70
Russia	0.245	1.807	-16.02	-0.002	0.097	-10.44
Turkey	0.413	2.785	-25.12	-0.001	0.099	-14.49
Germany	0.157	1.654	-4.88	-0.001	0.063	-11.66
Japan	0.012	2.225	-10.19	0.000	0.053	-9.68
US	0.080	0.686	-3.08	0.000	0.045	-10.82

Notes: ADF is the augmented Dickey-Fuller unit root test statistic. (*) in a column heading implies statistical significance at the 1% level for all entries in the column.

[6] The system in Eq.(2) is estimated via a two-stage procedure as it requires restrictions imposed on a standard (symmetrical) VECM (the first stage is a Johansen estimation which does not allow to impose restrictions, the second stage is OLS); see Lütkepohl and Krätzig, 2004, Ch.3, for details.

[7] Due to data availability, the beginning of the sample period differs for the following countries: Bulgaria (November 2000), Croatia (June 2002), Slovenia (June 2002), Ukraine (October 2001). For Turkey, we exclude the 2001 February crisis and set our sample period to start from July 2001.

As outlined above, the first step of the analysis is the cointegration test. Table 2 reports the results of a bivariate Johansen cointegration (Trace) test between *IP* and *S* in each country. When the lag length used in the Johansen cointegration test is optimized by the Hannan-Quinn information criterion, we find a significant cointegrating vector in four countries. However, in our VARwAL model, we employ 10 lags. An important issue, which has so far been not much elaborated on in the literature, is the that the dynamic lags and the EC term compete against each other to capture the parameters of the convergence to the equilibrium relationship. Therefore, in most cases, the cointegrating relationship disappears with the inclusion of 10 lags. On the other hand, the cointegrating vector becomes significant under 10 lags in US, whereas it was not under the standard optimized lag length. Thus, in the following analysis, two countries (Turkey and US) require a VECwAL model, while for all other countries we will proceed with the VARwAL model.

Presence or absence of cointegration in these test results is difficult to associate with market characteristics of interest: for example, under the standard lag length optimized by the Hannan and Quinn criterion, none of the developed markets bear a significant cointegrating relation, whereas three frontier markets do.

Table 2. Cointegration test results

	Lag set by HQ criterion			10 lags	
Country	**LR**	***p*-val**	**trend**	**LR**	***p*-val**
Bulgaria	48.81*	0.000	Y	23.18	0.104
Croatia	20.86	0.040	N	17.56	0.114
Estonia	15.83	0.514	Y	17.13	0.413
Latvia	19.40	0.263	Y	17.02	0.421
Lithuania	43.96*	0.000	Y	23.25	0.102
Romania	14.83	0.241	N	14.68	0.251
Slovenia	37.47*	0.001	Y	28.15	0.023
Ukraine	8.41	0.788	N	10.32	0.615
Czech R.	16.14	0.489	Y	17.04	0.420
Hungary	27.08	0.033	Y	18.13	0.343
Poland	35.26*	0.002	Y	25.99	0.046
Russia	24.37	0.011	N	14.65	0.253
Turkey	15.31	0.214	N	13.40	0.340
Germany	21.49	0.032	N	23.05	0.018
Japan	17.22	0.126	N	16.24	0.166
USA	19.08	0.071	N	27.06*	0.004

Notes: This table reports the Johansen Trace test results. LR is the likelihood ratio test statistic, the second column reports the associated *p*-values for the null hypothesis of zero cointegrating vector. The third column designates whether the trend term was included or not in the final version of the test, which gives the lowest *p*-value. The left block reports the test results under the optimal lag length suggested by the Hannan-Quinn criterion which ranges between 1 and 5; the right block reports the results under 10 lags, which is the specification employed in our VARwAL/VECwAL model. (*) denotes significance at the 1% level.

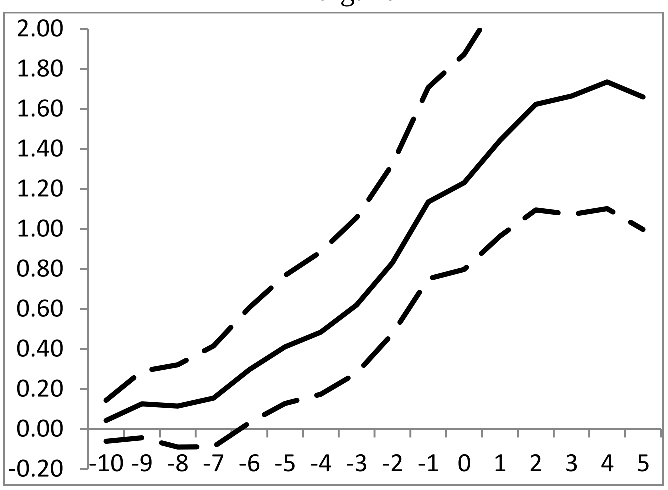
3. Results

We standardize G and R to have zero mean and unit standard deviation before using them in Equation (1). Thus, the results are directly comparable across countries, and represent the cumulative response of stock market returns in standard deviations to a 1-standard deviation shock in industrial production. This information can be useful in calibrating present value models. Figure 2 depicts the cumulative response of R from month –10 up to month +4 to a shock in G in month 0, derived from the estimation of the VARwAL specification described in Eq.(1), along with 90% confidence bands.[8] For Turkey and US, where a cointegrating vector is found to be significant, the impulse-response comes from the VECwAL specification described in Eq.(2). The presentation in Figure 2 enables an intuitive interpretation, that resembles to event studies widely used in the finance literature.

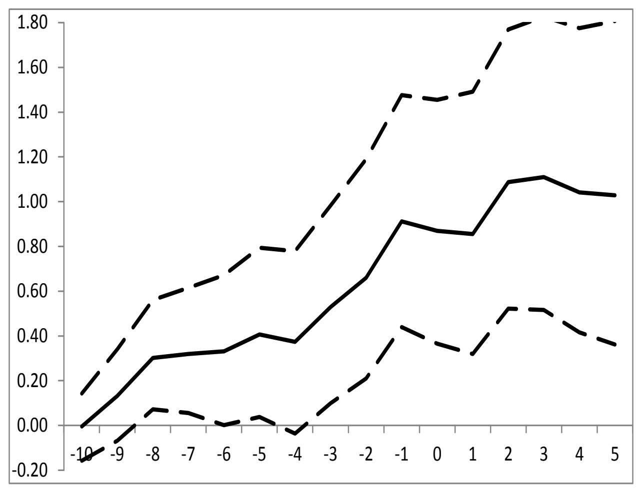
Figure 2. Impulse-responses from the VARwAL/VECwAL model

Panel A. European frontier markets

Bulgaria



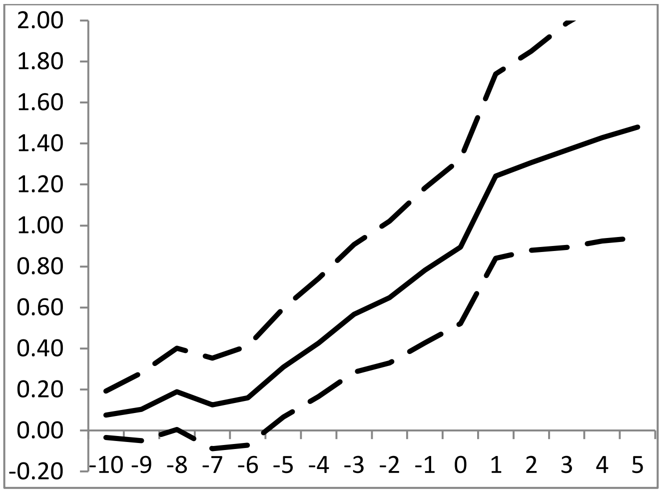
Croatia

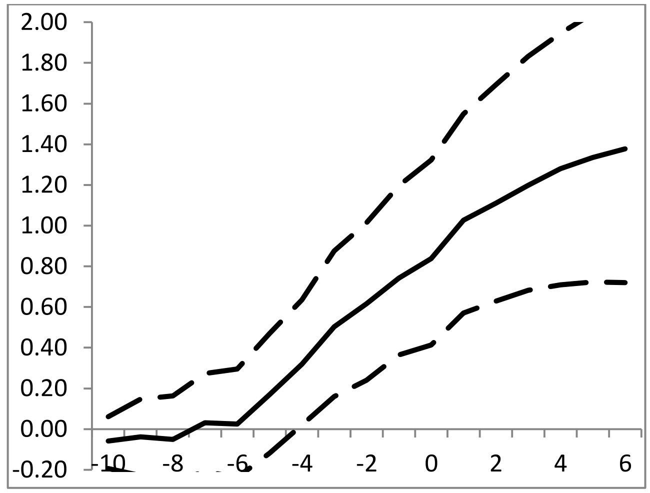


Estonia

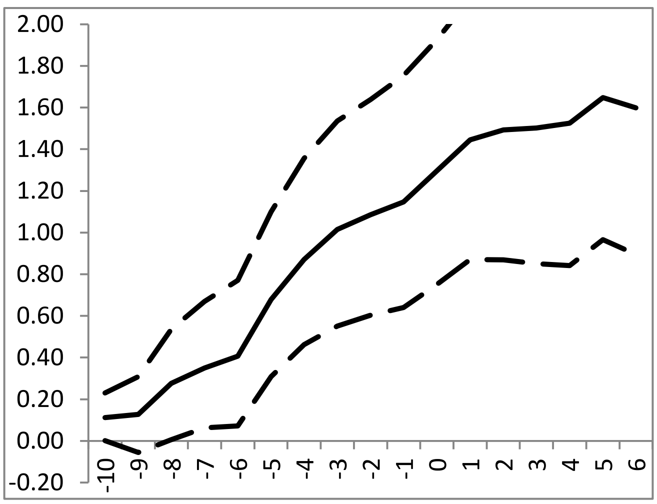
Latvia

[8] In a few cases, the impulse-response graph is extended up to month +6 or +7 in order to confirm the point where the cumulative impulse-response stabilizes.

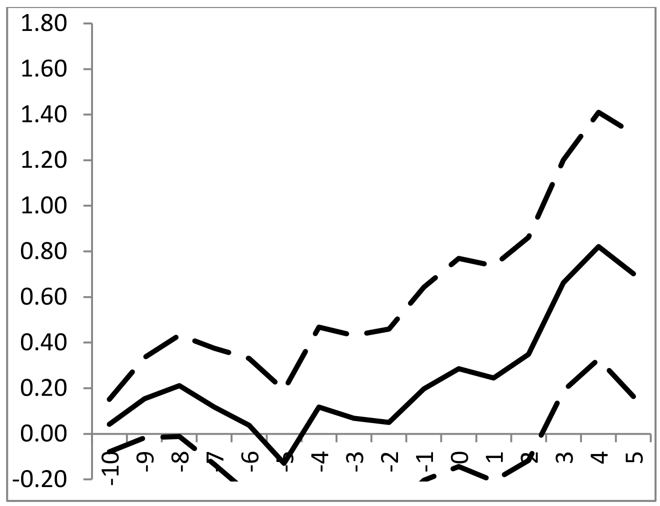




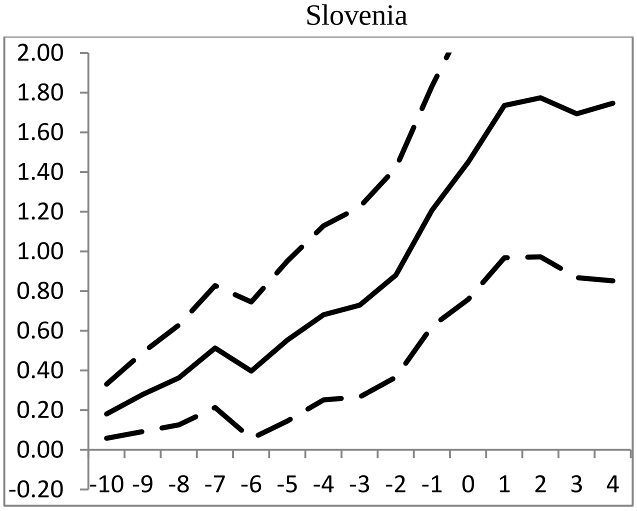
Lithuania



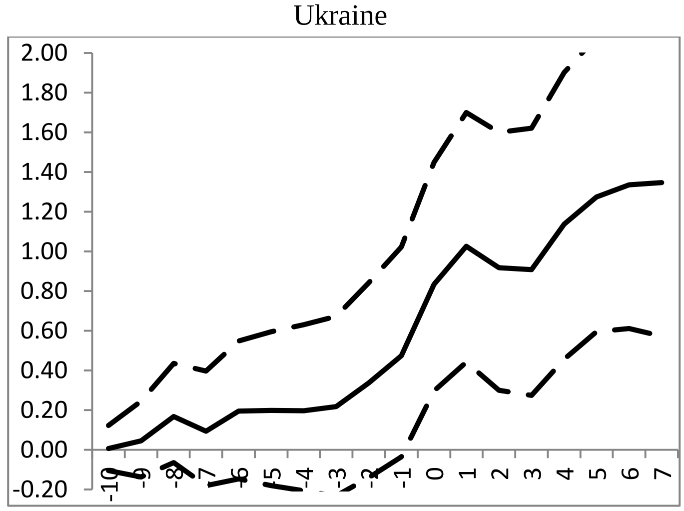
Romania



Slovenia

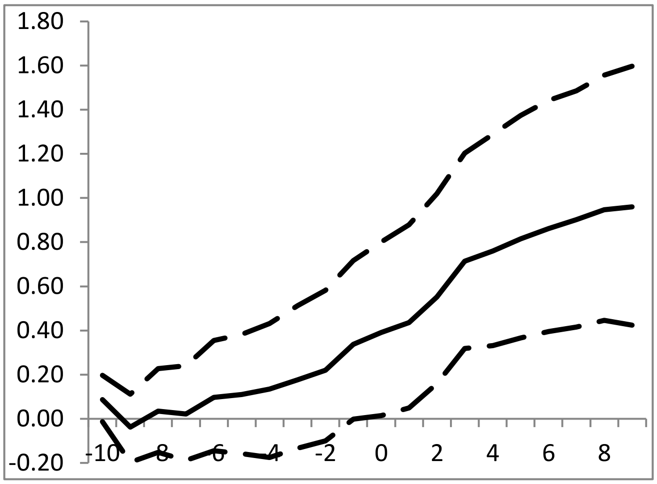


Ukraine

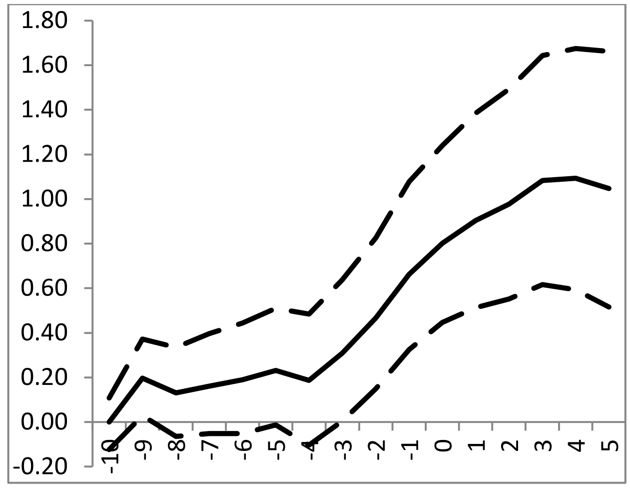


Panel B. European emerging markets

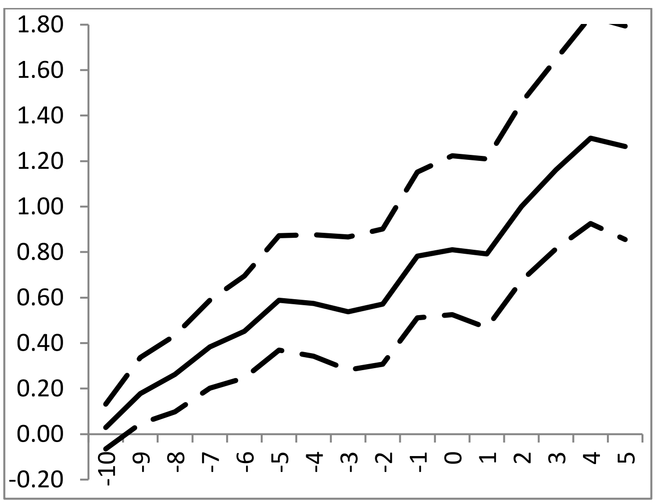
Czech R.



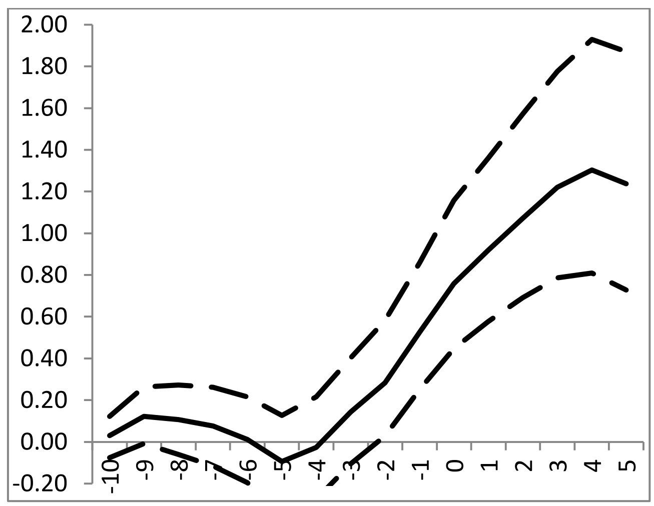
Hungary



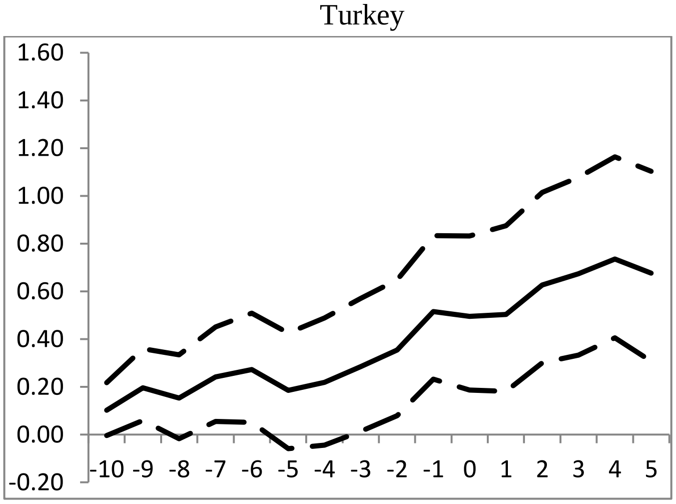
Poland



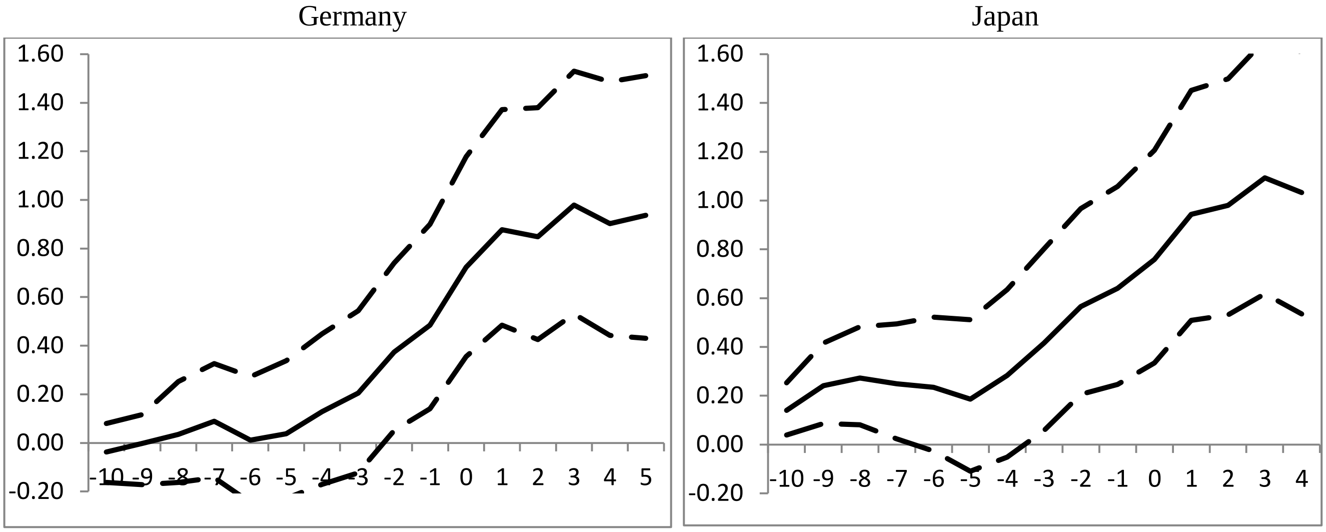
Russia



Turkey



Panel C. World’s most developed markets



Notes: The solid line in the middle depicts the cumulative impulse-response coefficients of stock market real returns (*R*) to a shock in real industrial production growth (*G*) in month 0, derived from the VARwAL/VECwAL models, described in Eq.(1) and (2), respectively. The dashed lines represent 90% confidence band obtained from a bootstrap simulation following the procedure described in Hall (1992). Since *G* and *R* are standardized to have zero mean and unit standard deviation at the country level, cumulative impulse-response coefficients are comparable across countries. The vertical axis shows the cumulative impulse-response in standard deviation units; the horizontal axis shows the months. The result for US is depicted in Figure 1.

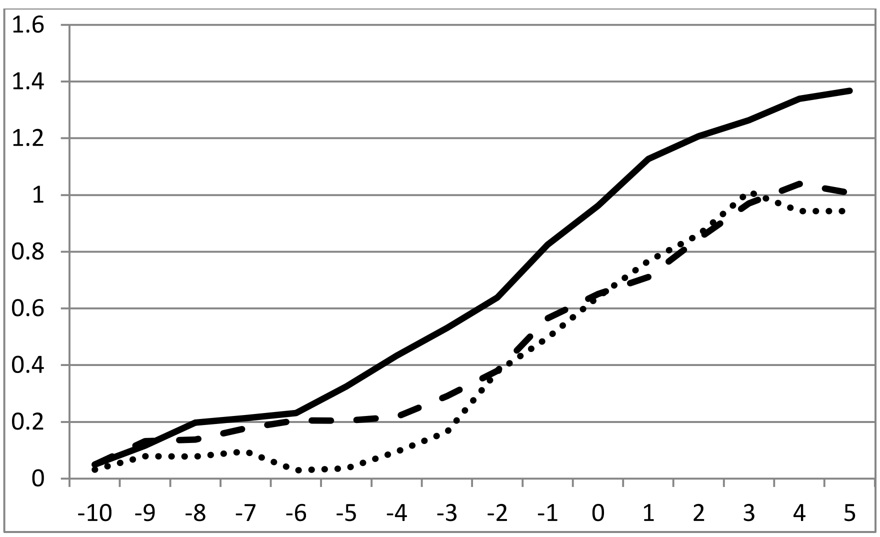
A first overall observation from Figure 2 is that for all countries we have both a number of significant forward-looking coefficients before month 0 and a number of significant delayed response coefficients after month 0. (The significance of individual lags is assessed based on non-cumulative impulse-responses, available from the authors). This feature does not appear to differ between frontier, emerging and developed markets. Significance of delayed response coefficients confirms the efficacy of our approach: stock market’s response to a real output shock in month 0 is not completed by month 0. Failure to allow a delayed response leads to omission of a nontrivial part of stock market’s response and amounts to excluding the possibility of a delayed response, which would be a specification error. Thus, the first contribution from our results is to document the significance of lagged responses, and to highlight the necessity of allowing lagged responses in the econometric specification.[9]

The second message from Figure 2 is that all countries have highly similar patterns of stock market’s response to real output shocks. The cumulative response is monotonically increasing in all countries from around months -7 and -5 until month +3 or +4, with only minor exceptions. Only one country’s (Romania) stock market seems display a relatively laggard response. On the other hand, despite the overall similarity, the magnitude of the cumulative response seems to increase as one moves from developed markets to frontier markets. Below, we characterize the differences between these three groups in more detail.

[9] For Japan, controlling for the impact of the tsunami in March 2011 does not affect the result (available from the authors).

Figure 3 provides a visually-appealing comparison between the three groups (European frontier-, European emerging- and world's most developed markets) in terms stock market's response pattern. Note that since the *G* and *R* series were standardized, the impulse-response coefficients can be averaged across country-groups. In response to a 1-standard deviation real output shock in month 0, developed stock markets display approximately 1-standard deviation cumulative return response. This result is quite encouraging from the perspective of calibrating present value models.[10] The cumulative response of European emerging markets is only slightly larger. The average cumulative response of European frontier markets is considerably larger (by approximately 30%). Thus, the magnitude of the total cumulative response appears to be a distinguishing characteristic: European frontier stock market returns are relatively more volatile in proportion to their real output volatility. One potential reason for this can be that the small size restricts the scope of diversification within the country. Another possibility is that lack of market depth may be exaggerating stock market responses to information. Under the terms of consumption-based asset pricing model, this can be interpreted to represent a lower elasticity of intertemporal substitution, which may result from a higher degree of risk aversion. Note that most of the difference emerges during the forward-looking part of the response.

Figure 3. Cumulative stock market responses compared



Notes: The solid, dashed and dotted lines represent the average cumulative impulse-response coefficient for the European frontier, European emerging, and world's developed market groups, respectively.

An important aspect of the comparison is in terms of stock market's forward-looking characteristic. The results in Figure 3 suggest little difference between the three groups in terms of the decomposition of the forward-looking and delayed responses. We also construct a more precise measure of stock market's forward-looking characteristic, utilizing information from our cumulative impulse-response functions (CIRF). As the

[10] Note that we do not control for discount rate changes in this analysis. The discount rate is likely to be endogenous to real output shocks. For a complete calibration, the response of the discount rate to real output shocks needs to be considered.

industrial production statistics pertaining to month 0 is announced within month 1 in all countries, stock market's cumulative response by the end of month 0 can be defined as forward-looking. Let us define $CIRF^{max}$ as the maximum level of CIRF within the range of months from -10 to +5. Typically $CIRF^{max}$ is observed somewhere between months +1 and +5. Then, the $CIRF_0$ / $CIRF^{max}$ ratio can be interpreted as a measure of the *forward-lookingness* of the stock market. This ratio can vary within a range of [0.1]. The first column of Table 3 reports this ratio, along with the average values for the three groups of countries. The frontier, emerging and developed market groups do not visibly differ in terms of their forward-lookingness as measured by this ratio, with group averages close to each other. In all groups on average 0.62-0.66 of the total response of the stock market is completed by the end of the month in which the real output shock occurs. Romania stands out with the lowest ratio. Interestingly, US has the second lowest ratio. This figure might have been influenced by the 2008 crisis, and might be an indication of how surprised the market participants were by the events during the crisis. Czech R., for which Hanousek and Filer (2000) report a looser stock market - real output connection and attribute it to the voucher privatization, features the third lowest ratio.

Table 3. The forward-lookingness indicator

Country	$CIRF_0$ / $CIRF^{max}$		$CIRF_{-4}$ / $CIRF^{max}$		$CIRF^{max}$	
Bulgaria	0.71		0.28		1.73	
Croatia	0.78		0.34		1.11	
Estonia	0.60		0.29		1.48	
Latvia	0.63		0.24		1.34	
Lithuania	0.79		0.53		1.65	
Romania	0.35		0.14		0.82	
Slovenia	0.80	Frontier avg.	0.38	Frontier avg.	1.81	Frontier avg.
Ukraine	0.65	0.66	0.15	0.29	1.27	1.40
Czech R.	0.48		0.16		0.82	
Hungary	0.73		0.17		1.09	
Poland	0.62		0.44		1.30	
Russia	0.58	Emerging avg.	-0.02	Emerging avg.	1.30	Emerging avg.
Turkey	0.67	0.62	0.30	0.21	0.74	1.05
Germany	0.74		0.13		0.98	
Japan	0.68	Dev. avg.	0.25	Dev. avg.	1.07	Dev. avg.
USA	0.46	0.63	-0.13	0.08	0.96	1.00

Notes: $CIRF_0$ is the value of the $G \rightarrow R$ cumulative impulse-response function in month 0; $CIRF^{max}$ is the maximum value of the $G \rightarrow R$ cumulative impulse-response function between months –10 and +5. The average values for the three groups of countries are reported at the bottom of their respective panel. A higher $CIRF_0$ / $CIRF^{max}$ ratio implies that the stock market completes a larger proportion of its total response to output news

Stock market's forward-looking response can result from two mechanisms: i) stock market may respond to factors that will also drive economic growth, ii) stock markets may monitor economic activity and respond to early signals of it. We hypothesize that these two mechanisms can be distinguished by the time distance between the stock market response and real output shock: too early responses are likely to reflect the former mechanism, while nearby responses may be due to the latter mechanism. Even though it is difficult to set a precise border between these two mechanisms, one may classify stock market responses from month –3 through 0 as driven by information derived from signals of current business activity and/or decisions for near-future activity, whereas responses between months –10 and –3 are more likely to be driven by responding to structural factors that also happen to shape economic activity (e.g., EU accession, reforms such as market opening to FDI, etc.). Failure to distinguish between these two mechanisms may lead to overestimating the relative forward-lookingness in transition economies.

For this purpose, the second column of Table 3 reports the $CIRF_{-4}$ / $CIRF^{max}$ ratio where $CIRF_{-4}$ is the $G \rightarrow R$ cumulative impulse-response as of the end of month –4. As suspected, frontier markets feature a higher $CIRF_{-4}$ / $CIRF^{max}$ ratio. Hence, a large part of frontier markets' forward-lookingness seems to result from structural factors. The ($CIRF_0$ – $CIRF_{-4}$) / $CIRF^{max}$ ratio would then serve as a measure of stock market's ability to respond to early signals economic activity. This is where factors that drive market efficiency such as transparency of corporate information, wealth of early economic indicators such as business and consumer sentiment indices, presence of speculators willing to act on economic activity signals and the transaction costs which, if too high, may handicap their function play a role. Although the ($CIRF_0$ – $CIRF_{-4}$) / $CIRF^{max}$ ratios are not separately reported in Table 3, it is easy to derive them from the difference between the first and second columns. The results indicate the highest difference for developed markets, whereas the smallest difference is observed for frontier markets. Thus, a relatively smaller proportion of stock market's forward-lookingness in frontier markets comes from responding to early signals of economic activity, whereas for developed and emerging markets such near-forward response, which presumably results from monitoring signals of activity, plays a much larger role. Intuitively, this can be attributed to the presence of speculators trading on early information signals, lower transaction costs, wider availability of sentiment indexes and a higher degree of information flow due to better transparency.

The $CIRF_{-4}$ estimate for US at –0.13 is certainly interesting. A negative interim cumulative impulse-response coefficient can be an indication of stock market bubbles (this is because the stock market moves in opposite direction to the real output shock that will occur in the future). While –0.13 may be not sufficiently significant to claim a bubble, this figure may be related to the bubble-like environment that prevailed in 2000 and 2007 before the two major crises. US also exhibits one of the largest delayed responses (i.e., from month 1). We tend to interpret a delayed response to indicate market's failure to predict extraordinary events that lead to unusual shock persistence, such as the 2008 crisis in US. Apparently, the 2008 crisis had so pervasive effects which came at their surprise that the link was re-established with a delayed reaction of the stock market. Russia also stands out with a $CIRF_{-4}$ estimate near zero. The may result from energy sector's dominance in the Russian economy which makes it dependent on global oil price.

The last column of Table 3 reports the magnitude of stock markets' cumulative response as measured by $CIRF^{max}$. As observed from Figure 3, the total cumulative response is substantially larger in frontier markets than in developed and emerging markets. This may be an outcome of structural changes that drive both the stock markets and economic activity.

4. Conclusion

The interaction between the stock indexes and aggregate output is not symmetrical in terms of time order; thus, it requires an asymmetric VAR/VEC specification. This article proposes VARwAL and VECwAL models as the most suitable specification to study stock market – real output interaction. The article also presents the first comprehensive study of the stock market – real output relationship in Eastern Europe's young frontier markets. A comparison to relatively more active European emerging markets and world's largest developed equity markets enables us to examine the role of market development in determining forward-looking characteristics (i.e., leading indicator function) of the stock market.

Our results point to the efficacy of the methodological approach proposed in this article. In all counties studied, the stock market displays a significant delayed response. Thus, empirical models that exclude a lagged response of the stock market, as in Fama (1990), are incomplete. While a caveat is necessary here as our sample period contains a significant global crisis that seems to have caught all stock markets by surprise and caused delayed responses, our results clearly suggest that the econometric specification must allow for a delayed response. Our results also indicate that a naïve implementation of cointegration test would lead to misleading conclusions on whether the stock market is disconnected from the real economy. Our approach suggests, regardless of absence or presence of a significant cointegrating relationship, very similar stock market behavior across all countries with only minor differences.

Specifically, in almost every country, both forward-looking and delayed responses are significant, which is similar across these three categories of markets. Our findings are consistent with Mauro's (2003) conclusion that "the proportion of countries in which the correlation (between output growth and lagged stock returns) is significant is the same for emerging market economies as it is for advanced economies using yearly data, and somewhat lower using quarterly data". Our approach makes such a conclusion clearer to pinpoint. However, our results also uncover systematic differences. The magnitude of the cumulative response is larger in frontier markets. Furthermore, a larger part of the cumulative response in frontier markets comes in a distant-horizon forward-looking manner. This is likely to result from structural changes in the economy such as EU accession or structural reforms. In contrast, developed markets feature larger near-horizon forward-looking responses, which likely reflect informational market efficiency.

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Appendix A

In a standard VAR setting,

$$G_t = \omega_1 + \sum_{i=-10}^{-1} \psi_i G_{t+i} + \sum_{j=-10}^{-1} \theta_j R_{t+j} + \varepsilon_{1,t} \qquad (1)$$

$$R_t = \omega_2 + \sum_{i=-10}^{-l} \gamma_i G_{t+i} + \sum_{j=-10}^{-1} \lambda_j R_{t+j} + \varepsilon_{2,t} \qquad (2)$$

By imposing the contemporaneous impact of current stock returns, R_0 and the lead effects of expected future stock returns, $\hat{R}_{t+j}$ on industrial growth, equation (1) can be extended as

$$G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{-1}\theta_j R_{t+j} + \theta_0 R_0 + \sum_{j=1}^{4}\theta_j \hat{R}_{t+j} + \varepsilon_{1,t} \qquad (3) \text{ where } R_{t+j} = \hat{R}_{t+j} + \eta_{t+j}$$

Then,

$$G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{-1}\theta_j R_{t+j} + \theta_0 R_0 + \sum_{j=1}^{4}\theta_j (R_{t+j} + \eta_{t+j}) + \varepsilon_{1,t}$$

$$\Rightarrow \quad G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{-1}\theta_j R_{t+j} + \theta_0 R_0 + \sum_{j=1}^{4}\theta_j R_{t+j} + \sum_{j=1}^{4}\theta_j \eta_{t+j} + \varepsilon_{1,t}$$

$$\Rightarrow \quad G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{-1}\theta_j R_{t+j} + \sum_{j=0}^{4}\theta_j R_{t+j} + \sum_{j=1}^{4}\theta_j \eta_{t+j} + \varepsilon_{1,t}$$

$$\Rightarrow \quad G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{-1}\theta_j R_{t+j} + \sum_{j=0}^{4}\theta_j R_{t+j} + \xi_{1t} \quad (4) \qquad \text{such that } \xi_{1t} = \sum_{j=1}^{4}\theta_j \eta_{t+j} + \varepsilon_{1,t}$$

By imposing (4) in a VAR setting, we introduce the VARwAL form as follows

$$G_t = \omega_1 + \sum_{i=-10}^{-1}\psi_i G_{t+i} + \sum_{j=-10}^{4}\theta_j R_{t+j} + \xi_{1t}$$

$$R_t = \omega_2 + \sum_{i=-10}^{-5}\gamma_i G_{t+i} + \sum_{j=-10}^{-1}\lambda_j R_{t+j} + \varepsilon_{2,t} \qquad (5)$$

Note that the lag structure corresponding to (5) is G_{t+i} is modified due to the redundancy of parameters.

Thus, the system in (5) can be expressed in matrix form such that,

$$\boldsymbol{Y} = A\boldsymbol{X} + U$$

where A is a restricted coefficient matrix that satisfies $\boldsymbol{\alpha} = R\delta$ and $\boldsymbol{\alpha} = vec(A)$, δ is the vector of all unrestricted parameters. Then an GLS estimator of δ is provided in Luetkepohl, 2009 such that

$$\hat{\delta} = [R'(\boldsymbol{YY'} \otimes \Sigma_u^{-1})R]^{-1}R'(\boldsymbol{Y} \otimes \Sigma_u^{-1})vec(Y)$$

which is consistent and asymptotically distributed, $\sqrt{T}(\hat{\delta} - \delta) \xrightarrow{d} N\left(0, \left(R'\Sigma_{\hat{A}}^{-1}R\right)^{-1}\right)$. The corresponding feasible GLS estimator $\hat{\boldsymbol{\alpha}} = R\hat{\delta}$ is also consistent and normally distributed (see Luetkepohl, 2009 p.14).

Moreover, VECwAL can be introduced for those systems with a cointegrating vector as follows.

$$\boldsymbol{Y} = \alpha\beta'\boldsymbol{C} + A\boldsymbol{X} + U$$

Here, $\boldsymbol{C}$ is the cointegrating vector, β is the cointegrating parameter, and α is the speed of adjustment parameter. The feasible GLS estimators of α and β converge at the usual rate $\sqrt{T}$ to an asymptotic normal distribution under general conditions (see Ahn and Reinsel (1990) and Saikkonen (1992)).