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THE IMPACT OF THE RUSSIA-UKRAINE WAR ON
THE FOOD INDUSTRY: A NETWORK APPROACH

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Abstract

This paper applies the event study methodology on a global set of firms in the food industry, focusing on the outbreak of the Russia-Ukraine war. Abnormal returns are estimated from daily stock data of the firms using a market model and are analyzed both in their aggregated forms and in firm-level regressions. The two hypotheses of the study are 1) that a large set of companies experienced significant negative abnormal returns around the event and 2) that the spillover effects from Russia and Ukraine towards other firms caused higher negative abnormal returns. The spillover impact variables are estimated with a network structure by a pairwise Granger-causality method. Results support both hypotheses: significant negative aggregated abnormal returns could be observed both by Sectors and Regions; also, the spillover effect variable is significant with a negative coefficient even after controlling for financial variables that are commonly used factors.

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1 Introduction

Global food inflation has reached historical highs in 2022 after existing price pressures have been accelerated by the outbreak of the Russia-Ukraine war ([Bodnár & Schuler, 2022](#); [OECD, 2023](#)). Besides the obvious implications of the conflict on raw materials and the energy sector – primarily fossil fuels – the impact on the price of food commodities and agriculture products have wide consequences as well. As for the European Union, while the aggregate exposure of the agricultural sector is not too high, there are several significant direct exposures due to the heterogeneity of the countries and markets. For example, around one third of cereals is imported from Russia and Ukraine combined, pressuring prices in the supply chain of dairy and meat products, impacting a wide range of companies ([Eurostat, 2022](#)). Of course, this exposure is not limited to the EU – [Abay et al. \(2023\)](#) emphasize the global relevance of the conflict and identify for example the vulnerability of the Middle East and North Africa regions .

We propose to examine these global effects of the war on firm-level market data. In an event study framework, we analyze abnormal returns around the event date, which is 2022/02/24, the outbreak of the war. We supplement the study with a cross-sectional analysis to explain firm-level variations of abnormal returns, including the effect of the exposures to the Ukrainian and Russian markets. Our two hypotheses are the following: 1) that companies in the food producer, beverages and food retailer sectors experienced significant negative abnormal returns on and around the event date and 2) that firms with significant spillover effects from Russia and Ukraine show higher negative abnormal returns.

The construction and methodology of the event study mainly follows [MacKinlay \(1997\)](#). The expected returns are estimated using a market model with OLS regressions. The abnormal returns (ARs) are given by the deviations of observed returns from the expected returns. Aggregated ARs can be calculated over time and across groups of companies to summarize the impact of the war on a given Sector or Region. Test statistics allow for testing the hypothesis whether the abnormal returns are significantly different from zero. In the cross-sectional analysis, besides various financial variables, we estimate a spillover effect variable of the Ukrainian and Russian markets based on the spillover network approach of [Billio, Getmansky, Lo, and Pelizzon \(2012\)](#) using pairwise Granger-causality connections.

Results show that all three sectors show significant negative aggregated abnormal returns, even up to the $[-10, 10]$ day event window. As for the regions, all of them except North America present negative significant aggregated abnormal returns on the event day. However, they do differ in persistence: as expected, the Europe & Central Asia region shows both the highest and most persistent negative ARs. The cross-sectional regressions show that the spillover effect from Russia and Ukraine is negative and significant in all specifications, even after controlling for all financial variables.

Section 2 summarizes first the literature of event studies in general, then more specifically the recent results concerning the Russia-Ukraine war. Section 3 provides information on the data sources and the steps of data cleaning. Section 4 contains the description of methodology, from steps of the event study to the definition of the spillover network and cross-sectional variables. Section 5 summarizes the results of the analysis, focusing on the aggregated abnormal returns and the firm-level regressions. We conclude our findings in section 6.

2 Literature review

2.1 Event studies

The motivation of event studies is summarized in [MacKinlay \(1997\)](#): in short, researchers often want to measure the effect of an event on for example firms or commodities. Event studies may be used in finance research to analyze mergers and acquisitions, announcements or changes in legislation when applied in law and economics research. That is one of the early papers to provide a comprehensive summary of the structure of an event study, of different methods and of the derivation of abnormal returns and the corresponding test statistics. Another study focuses on the statistical properties of the estimated abnormal returns along the issues that may arise with them ([Brown & Warner, 1985](#)). Event studies are most frequently performed on the price and return data of equities, market and commodity indices. In the next subsection, we summarize the recent literature that concerns the Russia-Ukraine war.

2.2 Russia-Ukraine war

Across the event study literature, various sectors and industries have been analyzed since the outbreak of the war, with significant impacts detected in financial and commodity markets, including food, energy and raw materials - the industries mostly connected to Russia and Ukraine. Studies (e.g. [Lo, Marcelin, Bassène, & Sène, 2022](#)) explore the country-level variations in impact based on the trade dependence of countries, measured by the energy and food exposure to Russia. [Ahmed, Hasan, and Kamal \(2022\)](#) note that the stock returns vary according to the industry, country and size of the company, they also stress the importance of $[-3]$ day of the event window, the date of recognition of the two regions of Ukraine as autonomous by Russia. Also, connections between individual commodities and geopolitical factors are analyzed in [Saâdaoui, Ben Jabeur, and Goodell \(2022\)](#), who conclude that geopolitical factors significantly impact food prices. In the analysis of commodity indices, [Umar, Riaz, and Yousaf \(2022\)](#) show that clean energy indices – being a substitute of conventional energy – experienced high positive abnormal returns in the attempt of investors to find safer investments that are less connected to Russia or Ukraine.

The cross sectional analysis of abnormal returns relies on a firm-level sample (as the number of commodity indices is limited). The literature summarized above considered only country or commodity-level variations in the impact of the war. Here, we review results of recent firm-level event studies. [M. Sun, Song, and Zhang \(2022\)](#) analyze a sample of firms from a wide range of countries to show the regional and sectoral differences in abnormal returns. [Abbassi, Kumari, and Pandey \(2022\)](#) find that companies are fragile to geopolitical risk and trade dependence, and also, that smaller firms outperform large ones. [Nerlinger and Utz \(2022\)](#) find in a cross sectional event study of energy firms that the companies in markets which compete with Russian energy outperformed the stock market around the event date, which implies the heterogeneity of the impact. [Federle, Müller, Meier, and Sehn \(2022\)](#) conclude that distance from Ukraine is a significant determinant of returns, with closer firms showing higher negative abnormal returns. This result is closely related to the concepts used in our paper, which will be discussed later in the Granger-causality estimated impact of the Russian and Ukrainian market.

3 Data

3.1 Data sources

The data utilized in this article was obtained from Datastream. The first search criterion for time series of stock prices comprised all companies worldwide that belong to the Food Producers, Beverages or Food and Drug Retailers sectors. The choice of these three sectors is strongly motivated by the paper’s goal of analyzing food market disruptions. Firms are not filtered based on their current activity (*Dead* or *Alive*) to account for survivorship bias (see [Brown, Goetzmann, Ibbotson, & Ross, 1992](#)). Instead of the regular closing prices of the firm stocks, we use the Total Return Index (RI). This is an adjusted price index that reflects the effect of dividend payments and describes a theoretical increase in share values when all dividends are reinvested. For all companies, the Return Index is denominated in US dollars. We calculate log returns from RI and apply them in both the event study and the Granger-causality estimation sections of the analysis.

The event study’s market model is based on a time series of market returns. Global market indices, industry-specific aggregates, or weighted averages generated from the data at hand are common options. First, we considered two series: the *MSCI World Agriculture & Food Chain Index* and the *S&P 500 Global Stock Index* adjusted closing price. Both are global indices denominated in US dollars, but we believe the MSCI industry-specific series will deliver more reliable results. That is why we use the Agriculture index throughout the analysis, which we also downloaded as Total Return Index from Datastream (MSWRAF\$ code). We obtained all daily price data for the period between 2021/03/01 and 2022/03/10.

For the cross-sectional analysis of abnormal returns, we choose to include several variables regarding the financial data of the companies. These are frequently used variables for the calculation of company size, illiquidity, analyst coverage, book value, as well as Price to Book and Price to Earnings measures. We downloaded the following daily time series datatypes for the first three months of 2022 (note, that currency-dependent variables are converted to US dollars and Datastream mnemonic codes are displayed in parentheses): Price to Earnings (PE), Price to Book Value (PTBV), Dividend Yield (DY), estimated Analyst Coverage (F1NE.I), Turnover by Volume (VO) and Market Value (MV). For the cross-sectional analysis, we only calculated static variables for the event day, which

requires only one observation. The last two financial variables are less frequently updated: we downloaded the June 2021 value for both Book Value per Share (WC05491) and Outstanding Shares (WC05301), which were the latest available values in February 2022.

Some general company characteristics are also available, such as the market, which is equivalent to the country of the relevant stock exchange, and the currency in which the equity is traded. Furthermore, Datastream offers a variety of industry classifications, depending on the level of diversification needed. One of these is the Industry Code by Datastream (WC06011), which is a four-digit code with the first two numbers representing a major industry group and the following two digits indicating the subcategories. Datastream also provides the mapping of industry names to the codes. Additionally, we considered two alternative industry classification systems. One is the I/B/E/S General classification (IBIND) and the other is the ICB Subsector (INDM5), which is the one with significantly less distinct categories.

3.2 Data cleaning

Data cleaning steps are necessary for two reasons: 1) to ensure that the event study algorithm runs without errors due to invalid data, and 2) to obtain accurate event study results by excluding firms with a high percentage of missing returns. The global scope is maintained throughout the analysis, as companies are not filtered by market. There are two criteria for the returns time series to ensure the reliability of Abnormal Return estimations. First, the company must have more than 100 days of observations in the estimation window, second, no missing values are allowed within the event window.

Since the number of omitted companies may differ according to the chosen length of the event and estimation windows, we only provide the number of firms remaining after each step in case of the $[-3, 3]$ event window and the 240-day long estimation window with no offset period between the two. Initially, time series of 6078 firms were present in the price data, which decreased to only 3807 companies after filtering for the estimation window requirements. After further cleaning based on the event window, 2184 companies remain in the sample. Note that for example, there are no Ukrainian firms in this sample. The reason for this is that the Ukrainian stock exchange closed on the 25th of February, 2022, right after the war broke out. Consequently, the data is missing for the next weeks, leaving the abnormal return calculations empty.

The analysis of aggregated abnormal returns is carried out on the full 2184-company sample, to maintain large enough subsets of the data for hypothesis testing. However, the sample used for the firm-level cross-sectional analysis is smaller because of missing values in the financial data. The model selection process, as well as the analysis of individual regression specifications is carried out on the same sample of 750 companies. Models estimated on the same data are directly comparable by means of information criteria, R^2 and individual coefficients of variables.

To find the most appropriate industry code for the 2184 companies in the final sample, we compared the number of distinct codes for each of the three classification systems, as well as the minimum, mean and maximum number of companies assigned to a given code, see Table 1 for results. Whereas the number of distinct categories is similar in case of the Datastream codes and the IBES General classification, the former seems more balanced with lower mean and maximum numbers. Therefore, throughout the cross-sectional analysis, we use the Datastream classification system.

Table 1: Comparison of industry classifications

We report key statistics regarding the three industry classification systems initially considered: the number of distinct codes, as well as the minimum, mean and maximum number of companies that belong to a given code. In terms of homogeneity and granularity, Datastream industry codes seem most suitable to use as control variables in the regressions as individual coefficients for each category are not important

Classification System	Distinct Codes	Min no.	Mean no.	Max no.
Datastream	75	1	205	422
IBES General	88	1	348	658
ICB Subsector	11	1	586	975

4 Methodology

The following chapter provides a summary of the methods used in carrying out the event study and constructing the dataset for the cross-section analysis of firms. We used the R language (version 4.0.4) for all our calculations ([R Core Team, 2021](#)). More specifically, the results are generated by the *erer*, *furrr*, *lmtest* and *estimatr* packages, and reported with *kableExtra* and *stargazer* – for detailed descriptions, see [Blair, Cooper, Coppock, Humphreys, and Sonnet \(2022\)](#); [Hlavac \(2022\)](#); [C. Sun \(2022\)](#); [Vaughan and Dancho \(2022\)](#); [Zeileis and Hothorn \(2002\)](#); [Zhu \(2021\)](#).

4.1 Event study

4.1.1 Market data and expected returns

In calculating the returns time series from the price index data, we used the formula for log returns following common practice. Based on the log-normality assumption of stock prices, returns calculated this way are also assumed to be normally distributed. Due to the logarithmic approximation, the R_{it} log returns are also close in value to the r_{it} simple returns.

$$R_{it} = \log(p_t) - \log(p_{t-1}) = \log\left(\frac{p_t}{p_{t-1}}\right) = \log(1 + r_{it}) \sim r_{it} \quad (1)$$

The structure of an event study begins with a model to estimate the normal returns. There are various approaches, but in this paper, we use the market model. Statistical methods like the market model are built on statistical assumptions only, not economic ones. The general equation of the market model takes the following linear form, where daily firm-level returns (R_{it}) are explained by returns corresponding to the chosen market portfolio (R_{mt}).

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (2)$$

$$\mathbb{E}(\epsilon_{it}) = 0 \quad \text{var}(\epsilon_{it}) = \sigma_{\epsilon_{it}}^2 \quad (3)$$

Following [MacKinlay \(1997\)](#), abnormal returns are indexed in the event window using τ where $\tau = 0$ on the event day. Let T_0 be the start of the estimation window, T_1 the event day and T_2 the last day of the event window. Then, the event window is indexed from $\tau = T_1 + 1$ to $\tau = T_2$, while the estimation window starts at $\tau = T_0 + 1$ and ends at $\tau = T_1$. The following notations are used in addition: the length of the estimation window is $L_1 = T_1 - T_0$ and the length of the event window is $L_2 = T_2 - T_1$. Expected returns within the event window are given by the estimated market model (see Eq. 4).

The ordinary least squares (OLS) method yields consistent estimators of the market model parameters under the usual assumptions ([Wooldridge, 2015](#)). Following the notations used by [MacKinlay \(1997, p.20\)](#), the parameter estimators for firm i are given by Equations (5)–(9).

$$\mathbb{E}(R_{i\tau}) = \hat{\alpha}_i + \hat{\beta}_i R_{m\tau} \quad (4)$$

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1} (R_{m\tau} - \hat{\mu}_m)^2} \quad (5)$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i \hat{\mu}_m \quad (6)$$

$$\hat{\sigma}_{\epsilon_i}^2 = \frac{1}{L_1 - 2} \sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \quad (7)$$

Where $\hat{\mu}_i$ and $\hat{\mu}_m$ are sample means of the firm-level and market returns:

$$\hat{\mu}_i = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{i\tau} \quad (8)$$

$$\hat{\mu}_m = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{m\tau} \quad (9)$$

4.1.2 Abnormal Returns

We can use the market model parameter estimates to derive and analyze Abnormal Returns (AR). It is simply the difference between the observed daily returns and the expected returns from the market model in the event window, which are equal to the out-of sample disturbance terms, $\epsilon_{i\tau}$.

$$AR_{i\tau} = R_{i\tau} - \mathbb{E}(R_{i\tau}) = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau} \quad (10)$$

Significance tests for the abnormal returns are based on the statistical properties of the market model OLS estimates. With the $AR_{i\tau}$ sample of L_2 length in the event window, the abnormal returns are jointly normally distributed under the null hypothesis, conditional on the event window market returns. The distribution has a zero conditional mean and a conditional variance that depends on the market model estimates (see MacKinlay, 1997, p.21). The formula for the variance consists of two terms. The first is invariant with respect to the time τ and is simply the variance of the disturbance term over the whole estimation window. The second term is necessary to adjust for sampling errors of $\hat{\alpha}_i$ and

$\hat{\beta}_i$ parameters. However, since this second term depends on L_1 and is asymptotically zero, when the estimation window is reasonably large, this component can be assumed to be zero (Eq. 11). For the hypothesis test on the distribution of ARs (see Eq. 12), the null hypothesis states that the observed abnormal returns are zero. The t-statistic for testing this H_0 is given by Equation (13).

$$\text{var}(AR_{i\tau}) = \sigma_{\epsilon_i}^2 + \frac{1}{L_1} \left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2} \right] \sim \sigma_{\epsilon_i}^2 \quad (11)$$

$$AR_{i\tau} \sim \mathcal{N}[0, \text{var}(AR_{i\tau})] \quad (12)$$

$$t_{i\tau}^{AR} = \frac{AR_{i\tau}}{\sqrt{\text{var}(AR_{i\tau})}} \quad (13)$$

4.1.3 Aggregated Abnormal Returns

The firm-level abnormal returns for each day in the event window can be aggregated by two dimensions: time and firm indices (based on market or country for example). In this section, we present the four aggregated AR measures with parameters of their assumed distributions and the corresponding test statistics on which our significance test are built (following MacKinlay, 1997, p.21).

Summing up the ARs across the event window yields the Cumulative Abnormal Returns (CAR) for each firm. The τ_1 and τ_2 indices are the start and end date of the Cumulative AR calculation that could be chosen to be any $T_1 < \tau_1 \leq \tau_2 \leq T_2$, but here, for simplicity, the CAR is calculated for the whole event window, so that $\tau_1 = T_1 + 1$ and $\tau_2 = T_2$.

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \quad (14)$$

With increasing L_1 estimation window length, the asymptotic variance of $CAR_i(\tau_1, \tau_2)$ is viable, because the second, time-dependent part of the AR variance formula was assumed to be zero. Therefore, the variance of CAR is simply the multiple of the AR variance, where the multiplier factor is the event window length (Eq. 15). Similarly to the abnormal returns above, the distribution of CAR values and the t-statistic to test the $H_0 : CAR = 0$ hypothesis are given by Equations (14) and (17).

$$\text{var}(CAR_i) = \sigma_i^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1)\sigma_{\epsilon_i}^2 = L_2\sigma_{\epsilon_i}^2 \quad (15)$$

$$CAR_i(\tau_1, \tau_2) \sim \mathcal{N}[0, \text{var}(CAR_i)] \quad (16)$$

$$t_i^{CAR} = \frac{CAR_i}{\sqrt{\text{var}(CAR_i)}} \quad (17)$$

Abnormal returns may be aggregated over groups of firms (for example by markets, industry categories or regions) or even across all firms. Here, we provide the formula for the Average Abnormal Returns (AAR), its variance, distribution and the corresponding test statistic in Equations (18)–(21). Let g be the index of the groups and N_g the number of firms in each specified group. From this point forward, the notations and formulae differ slightly from that of [MacKinlay \(1997\)](#).

$$AAR_{g\tau} = \frac{1}{N_g} \sum_{i=1}^{N_g} AR_{i\tau} \quad (18)$$

$$\text{var}(AAR_{g\tau}) = \frac{1}{N_g - 1} \sum_{i=1}^{N_g} (AR_{i\tau} - AAR_{g\tau})^2 \quad (19)$$

$$AAR_{g\tau} \sim \mathcal{N}[0, \text{var}(AAR_{g\tau})] \quad (20)$$

$$t_{g\tau}^{AAR} = \frac{AAR_{g\tau}}{\sqrt{\frac{\text{var}(AAR_{g\tau})}{N_g}}} \quad (21)$$

For the aggregation over both time and groups, we use the Cumulative Average Abnormal Returns (CAAR). The time indices are the same as in the CAR calculation above, with $\tau_1 = T_1 + 1$ and $\tau_2 = T_2$. The concept of grouping firms also applies here, similar to the AARs. Equations (22)–(25) provide the formulas for CAAR and the corresponding test statistic.

$$CAAR_g(\tau_1, \tau_2) = \frac{1}{N_g} \sum_{i=1}^{N_g} CAR_i(\tau_1, \tau_2) \quad (22)$$

$$\text{var}(CAAR_g) = \frac{1}{N_g - 1} \sum_{i=1}^{N_g} (CAR_i - CAAR_g)^2 \quad (23)$$

$$CAAR_g \sim \mathcal{N}[0, \text{var}(CAAR_g)] \quad (24)$$

$$t_g^{CAAR} = \frac{CAAR_g}{\sqrt{\frac{\text{var}(CAAR_g)}{N_g}}} \quad (25)$$

4.2 Network of companies

After the dataset of abnormal returns has been constructed for further cross-sectional analysis, there is a need to supplement the dataset with other firm-level characteristics other than the basic firm and industry information downloaded from Datastream. Our hypothesis regarding the cross-sectional analysis states that exposure to other firms from the Russian and Ukrainian markets makes companies more likely to present significant negative abnormal returns in the firm-level cross-sectional analysis. Based on this hypothesis, a framework is required where the connections and causal effects between individual firms can be empirically estimated.

The following part of the methods employed in this paper was inspired by the systemic risk and financial networks literature. Network analysis tools have often been used for estimating systemic risk and spillover effects on samples of firm securities, government bonds or even currencies. There are various methods to construct the network from the time series of the above financial instruments, for example simple correlations (e.g. [Coelho, Gilmore, Lucey, Richmond, & Hutzler, 2007](#); [Eryigit & Eryigit, 2009](#)), the Granger-causality connections ([Billio et al., 2012](#)) or the VAR model error variance decomposition (in [Diebold & Yilmaz, 2014](#)). The resulting network, or networks if the analysis follows a rolling window approach can be analyzed using network science tools: most frequently these include the centrality measures of nodes or distribution tests of the edge weights.

In this paper we use the pairwise Granger-causality approach to estimate bilateral links between firms which will construct the network. This approach, as described in detail for financial networks by [Billio et al. \(2012\)](#) is a relatively simple concept that yields a directed network - whether its edges are weighted or not can be chosen by us. To test for

significant Granger-causality, we will look at time series of two firms at a time, let these two random variables be notated by X_t and Y_t . The length and dates of the time series correspond to the estimation window used in the event study market model.

Two linear regressions are estimated and the difference in explanatory power is tested with a regular F -test. The first model (Eq. 26) is the unrestricted full specification, where lagged values of the X variable are also included along the Y terms up to the specified order, n . The second, restricted specification (Eq. 27) differs in that only lagged value of Y are used to predict Y_t . The F -test is carried out on these two specifications and variable X is said to Granger-cause Y when the H_0 of the F -test (that is, there is no increase in explanatory power between the two models) is rejected on the given significance level.

$$Y_t = \alpha + \sum_{i=1}^n \beta_i Y_{t-i} + \sum_{i=1}^n \gamma_i X_{t-i} + \epsilon_t \quad (26)$$

$$Y_t = \alpha + \sum_{i=1}^n \beta_i Y_{t-i} + \epsilon_t \quad (27)$$

In this paper, the outcome of the F -test is binary: it takes a value of 1 if the null hypothesis is rejected and 0 otherwise. The network is therefore unweighted, and the existence of an edge between node pairs depends on the outcome of the test. It is important to note that for a sample of around 4000 firms, the number of pairwise Granger-causality estimations needed to construct the complete network would be almost 16 million, which raises issues regarding computational intensity and long running times. This problem needs to be solved if we expect the network approach to be useful in the analysis.

The solution depends on the insight that most pairwise connections would be meaningless as they are expected to show no sign of significant causal relationship. Ruling these out after the complete network is constructed (by spanning trees or planar maximally filtered graphs) does not help, so it is necessary to filter connections before the calculations. Among various options, we chose to filter the pairs according to our hypothesis, that impact from Russian and Ukrainian markets corresponds to higher negative abnormal returns. In practice, when creating the full match between firm names, only those ones are preserved where the *from* names (the X variable in the above notation) are from these two markets.

Filtering at the first steps on the firm level (keeping the European continent for example) or deleting connections by other criteria, such as those where the two firms are not on the same continent would result in a similarly reduced network size. The firm-level variables constructed from the Russia-Ukraine market filtering process are the number of significant Granger-causality connections coming from either Ukrainian or Russian firms, or the two markets combined.

4.3 Spillover effect variables

We created three variables based on the Granger-causality spillover connections. In the previous section, we discussed how the potential network was filtered to only include connections that originate from the Ukrainian or Russian market. The potential connections were only filtered based on the criteria of enough (more than 100) estimation window observations, so that as many Ukrainian and Russian firms may be included. See Section 3.2 for issues regarding Ukrainian firms with further data cleaning. For a given firm, using the Granger-causality method, the F -statistic and p-value can be calculated for each pairwise connection, which is then compared to the $\alpha = 0.05$ significance level. Equation (28) introduces a function S on firms i and j , which returns 1 if company j significantly Granger-causes company i and 0 otherwise. The three firm-level variables are: the spillover effect from Ukraine (USE); Russia (RSE) or both markets combined ($URSE$). Equations (29)–(31) show the method to sum over the j companies of the given subset for each i .

$$S_{ij} = \begin{cases} 1 & \text{if } j \rightarrow i \quad (p \leq 0.05) \\ 0 & \text{if } j \nrightarrow i \quad (p > 0.05) \end{cases} \quad (28)$$

$$USE_i = \sum_{j \in \{\mathbf{UA}\}} S_{ij} \quad (29)$$

$$RSE_i = \sum_{j \in \{\mathbf{RU}\}} S_{ij} \quad (30)$$

$$URSE_i = \sum_{j \in \{\mathbf{UA}, \mathbf{RU}\}} S_{ij} \quad (31)$$

4.4 Financial variables

To use as control variables in the regression models, the following financial variables were calculated from the returns and other financial data described in Section 3.1. Company Size is given by the natural logarithm of Market Value (MV) and Analyst Coverage is the logarithm of the number of analysts who follow the company (+1 to avoid zeros within the logarithm). The illiquidity measure is given by the ratio of the daily return in absolute value, divided by turnover (Amihud, 2002). Momentum (see Jegadeesh & Titman, 1993) and Short-term Reversal (introduced by Jegadeesh, 1990; Lehmann, 1990) are cumulative sums of daily returns over the last 12 to 1 and last 1 month of the previous calendar year. Dividend Yield, Price to Book and Price to Earning ratios are directly used without transformation. See equations (32)–(36) for these calculations. The eight variables discussed so far are based on daily values, but we only calculated them for the event day for a static approach in the regressions. The last variable – Book Value – is less frequent and is based on only one observation, hence we drop the t index. It is calculated as the logarithm of the product of Book Value per Share and Total Shares Outstanding (Eq. 37).

$$CompanySize_t = \log(MV_t) \quad (32)$$

$$Analyst_t = \log(analysts_t + 1) \quad (33)$$

$$Illiquidity_t = \frac{|R_t|}{TURNOVER_t} \quad (34)$$

$$Momentum_t = \sum_{i=t-365}^{t-31} R_i \quad (35)$$

$$ShortRev_t = \sum_{i=t-30}^{t-1} R_i \quad (36)$$

$$BookValue = \log(BVshare * SharesOut) \quad (37)$$

Table 2: Aggregated Abnormal Returns:

Rows indicate the groups of companies by Sector or Region that each AR is based on. Columns display the Aggregated Abnormal Returns (AAR) for the event day (2022/02/24) and three days before, as well as the Cumulative AAR values for $[-3, 3]$, $[-5, 5]$ and $[-10, 10]$ day event windows. Every second row within a group displays the test statistic for the hypothesis test, where H_0 is that the corresponding AR would be equal to zero. AAR $[-3]$, AAR $[0]$ and CAAR $[-3, 3]$ are calculated from 2184 observations, which is the sample size for the $[-3, 3]$ event window specification. The number of observations for the CAAR $[-5, 5]$ and CAAR $[-10, 10]$ columns is 1921 and 1761 respectively.

	Type	AAR[-3]	AAR[0]	CAAR[-3,3]	CAAR[-5,5]	CAAR[-10,10]
Sector						
Beverages	AR	-0.0006	-0.0208	-0.0294	-0.0390	-0.0439
	t-stat.	-0.4649	-10.2603	-6.8093	-7.4718	-6.3966
Food and Drug Retailers	AR	-0.0050	-0.0154	-0.0427	-0.0526	-0.0346
	t-stat.	-4.3155	-5.5187	-6.3591	-6.3071	-2.6147
Food Producers	AR	-0.0016	-0.0223	-0.0261	-0.0261	-0.0331
	t-stat.	-2.7517	-15.3236	-10.5369	-8.3947	-8.9096
Region						
East Asia & Pacific	AR	0.0029	-0.0172	0.0022	0.0157	-0.0018
	t-stat.	3.7369	-14.5760	0.7886	4.0089	-0.3438
Europe & Central Asia	AR	-0.0038	-0.0318	-0.0513	-0.0626	-0.0655
	t-stat.	-5.5346	-16.1743	-14.2227	-15.5779	-12.4798
Latin America & Caribbean	AR	0.0061	-0.0054	-0.0163	0.0056	0.0175
	t-stat.	3.5972	-2.2746	-3.0678	0.8616	1.7447
Middle East & North Africa	AR	-0.0063	-0.0303	-0.0200	-0.0166	-0.0216
	t-stat.	-3.6320	-7.5356	-4.1833	-2.4923	-1.6052
North America	AR	-0.0055	0.0107	-0.0216	-0.0460	-0.0205
	t-stat.	-2.9301	3.5983	-4.0329	-4.8123	-1.5641
South Asia	AR	0.0036	-0.0241	-0.0302	-0.0424	-0.0172
	t-stat.	0.6456	-4.1183	-1.4596	-2.2836	-0.4134
Sub-Saharan Africa	AR	-0.0091	-0.0246	-0.0362	-0.0433	-0.0209
	t-stat.	-2.7072	-9.7080	-5.1794	-4.1423	-1.6614

5 Results

5.1 Abnormal Returns

In this section, we present the results of the abnormal return analysis. Table 2 shows the Aggregated ARs, where the companies were grouped by Sector and Region respectively. The aim of the table is to display how the aggregated ARs differ between these groups. We focus on the AARs of the event date $[0]$ and three days before the event $[-3]$, also the Cumulative AARs for the $[-3, 3]$, $[-5, 5]$ and $[-10, 10]$ event windows. We provide the corresponding test statistics, as described in Section 4.1.3, where the null hypothesis is that the given abnormal returns are zero. The number of observations decreases at wider event windows, as the filtering criteria depend on the estimation and event window.

Results in Table 2 show that negative abnormal returns are both higher and more per-

sistent in the Europe & Central Asia region. The $CAAR[-10, 10]$ value is significant for this region only, while values of the $AAR[0]$ and other cumulative ARs are highest among all regions. In general, more distant regions were less impacted by the war, nevertheless all but one of them display significant negative ARs. Note, that for North America, the abnormal returns compared to the market model were positive and significant, possibly indicating the flight of investors to the safer US markets. This latter result is consistent with [Boubaker, Goodell, Pandey, and Kumari \(2022\)](#), who studied the impact of the war on market indices and observed positive abnormal returns for the US index.

However, the cross-sectional analysis is based on firm-level abnormal returns, hence we present these results as well. Because of the high number of firms, we aggregate the results by ordering companies by their event day abnormal returns and partitioning the data into deciles. Table 3 shows the mean values of the $AR[0]$, important financial variables and all three spillover effect variables for each decile, with a structure similar to the one seen in [Bali, Cakici, and Whitelaw \(2011\)](#). Some results to note: Company Size is the smallest in the first decile; Analyst Coverage is much lower in both extremes; Momentum is the lowest in the first, Short-term Reversal is the highest in the 10th decile. Also, Dividend Yield is extremely high in the first decile and Price to Book Value is highest in the last decile. This indicates that these variables may drive abnormal returns in the lowest and highest 10% of the distribution.

5.2 Cross-sectional analysis

In Table 5, we report the results of different model specifications for cross-sectional firm-level regressions. The dependent variable is the event-day AR and the main independent variable is the combined spillover effect of the Ukrainian and Russian markets ($URSE$). These were chosen based on a model selection process (see Table 4), where all six combinations of the dependent and main independent variables are compared across the Base and Full model specifications. In the base model, only the $URSE$, region and industry variables are included. The Full model specification contains all financial variables above the Base model: Company Size, Analyst Coverage, Amihud Illiquidity measure, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value. To evaluate the model fit we used the Adjusted R^2 , as well as the Akaike (AIC) and Bayesian (BIC) information criteria.

Table 3: Deciles of firm variables, sorted by AR[0]

The distribution of event-day abnormal returns and company properties is displayed and sorted by the deciles of AR[0]. Variables used are the three spillover effects (URSE, USE and RSE) and financial variables: Company Size, Analyst Coverage, Amihud Illiquidity, Momentum, Short-term Reversal, Dividend Yield, Price to Book Value, Price to Earnings and Book Value. The table is split into two parts to accommodate all variables.

Decile	AR[0]	URSE	USE	RSE	Company Size	Analyst	Illiq.
1	-0.14	41.67	29.40	12.27	4.70	0.15	0.03
2	-0.06	40.01	28.88	11.13	6.03	0.44	0.01
3	-0.04	35.72	25.75	9.97	6.52	0.30	0.02
4	-0.03	32.88	23.25	9.63	7.32	0.66	0.00
5	-0.02	32.96	23.63	9.33	6.54	0.25	0.00
6	-0.02	30.49	21.57	8.92	7.11	0.37	0.00
7	-0.01	29.68	20.40	9.28	7.10	0.30	0.01
8	0.00	33.12	23.16	9.96	7.19	0.30	0.00
9	0.01	33.21	23.24	9.97	7.35	0.09	0.00
10	0.05	37.51	26.57	10.93	6.79	0.06	0.01

Decile	AR[0]	Momentum	ShortRev.	DY	PTBV	PE	BV
1	-0.14	-0.23	-0.01	9.04	2.13	43.83	11.38
2	-0.06	0.08	-0.01	2.54	2.97	35.34	12.33
3	-0.04	0.04	-0.01	2.93	4.22	36.16	12.62
4	-0.03	0.04	0.00	2.16	3.40	29.65	13.29
5	-0.02	0.02	-0.01	1.89	3.02	35.86	12.65
6	-0.02	-0.01	0.01	2.42	3.14	28.08	13.20
7	-0.01	-0.05	0.01	2.24	3.75	46.15	13.30
8	0.00	-0.01	0.01	2.44	3.37	28.04	13.18
9	0.01	-0.03	0.00	1.37	1.68	32.44	13.38
10	0.05	0.00	0.05	1.61	5.15	43.55	12.89

Results of the model selection show that regressing the AR[0] yields a better fit than the CAR[−3, 3] in each case. For the AR[0] model, the difference in fit between the Ukraine and Ukraine+Russia market impact forms is negligible, which means that the connections to Ukrainian firms alone is a more important factor than the connections to Russia. For the detailed regression tables, we choose to use the specifications where the dependent variable is AR[0] and the impact of both countries is considered. We can see that the optima differ according to the two information criteria, showing the tendency of AIC to tolerate models with more variables, whereas BIC punishes the degree of freedom more severely.

Table 5 is split to two parts, but the dependent variable and the main spillover variable is the same in both cases. Specifications in Column 6 are the same in both tables, this

Table 4: Model selection:

Each dependent variable, the event-day abnormal returns and the cumulative AR for the $[-3, 3]$ window is regressed on either the Ukrainian, Russian or combined spillover effects (USE, RSE and URSE variables). The base model only consists of the spillover effect, industry and region, while the full model includes all financial variables: Company Size, Analyst Coverage, Amihud Illiquidity measure, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value.

Impact	Method	AR[0]		CAR $[-3, 3]$	
		Base	Full	Base	Full
URSE	$adj.R^2$	0.25	0.27	0.15	0.25
	AIC	-2270.71	-2286.67	-1351.76	-1433.57
	BIC	-1979.64	-1954.03	-1060.70	-1100.93
USE	$adj.R^2$	0.25	0.27	0.15	0.25
	AIC	-2270.50	-2286.96	-1351.93	-1433.22
	BIC	-1979.44	-1954.32	-1060.86	-1100.57
RSE	$adj.R^2$	0.25	0.27	0.15	0.25
	AIC	-2267.86	-2282.07	-1349.87	-1430.07
	BIC	-1976.80	-1949.42	-1058.81	-1097.42

is included twice to allow for comparison between coefficients in simple models and the complete model. Note, that the *URSE* variable, as well as the Region and Industry factors are included in all models (these form the Base specification). Out of the nine additional financial variables, only one is added at a time, to see the individual coefficients and their significance level. For the last specification, we include all available variables at once. For the comparison to be valid, the number of observations remain the same across all models. T-statistics are reported below the coefficients for the standard H_0 , that the given coefficient equals zero. The t-statistics are calculated using White heteroskedasticity-robust standard errors of type 'HC1' (White, 1980).

Results show that the Ukraine+Russia spillover effect (*URSE*) on the observed abnormal returns is negative and significant in all specifications. The coefficient only varies slightly around -0.0004 , meaning that one additional significant incoming connection (as estimated by Granger-causality) from the two markets is expected to increase negative abnormal returns on the event date by ~ 0.04 percentage points (if we consider returns in percentages). Besides the *URSE* variable, the coefficients of several company-level financial variables were significant at the 5% level. The positive sign of Company Size implies

that larger firms in the food market suffered less negative abnormal returns. Analyst coverage, which is expected to correlate with company size exhibits the same connection its positive sign. The coefficient for Short-term Reversal, which measures the performance of the given equity over the last month, was also expected to have positive sign, as higher cumulative sum of returns signals a tendency of price increases. Consequently, lower values of Reversal would be associated with higher negative ARs. The positive sign of the Price to Book variable is somewhat counter-intuitive: from this, it seems that generally overvalued companies are expected to outperform others with less negative ARs. Finally, Book Value, which is another possible measure of company size, also shows that larger firms are expected to show less negative abnormal returns.

Comparing the above results with the full model, it shows some differences. The coefficients of Company Size, Price to Book and Book Value are no longer significant on the 5% level. This may be partly due to a multicollinearity between some of these variables, as Company Size and Book Value explain the same size concept, while Price to Book and Price to Earnings are both used for valuation. Regardless of this issue, the model selection tables show that the inclusion of all variables does not cause any major problems for the overall model performance, especially our main independent variable. The adjusted R^2 indicated that the variance of all X variables explains around 27.2% of the variance in $AR[0]$. The inclusion of other non-significant variables as controls is justified by the goal of the regression analysis to rule out other effects that may interfere with the effect of the *URSE* variable. Once the effects of the most frequently used financial characteristics of the companies on $AR[0]$ are accounted for, it corroborates the inference that the *URSE* is a significant determinant of negative abnormal returns.

Table 5: Regression results – AR[0]

Specifications where the dependent variable is the event-day abnormal return – AR[0]. Columns show the different specifications where the Base model includes the Ukraine-Russia market impact variable (*URSE*), as well as Region and Industry categories. Further models introduce variables to the model one-by-one: Company Size, Analyst Coverage, Illiquidity, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value. Individual coefficients for categories of Regions and Industry are not displayed. The number of observations is the same for all models. T-statistics are reported in brackets below the coefficients. We used White heteroskedasticity-robust standard errors of type 'HC1' (White, 1980).

<i>Dependent variable: AR[0]</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
URSE	−0.0004*** (−3.511)	−0.0003*** (−3.082)	−0.0004*** (−3.435)	−0.0004*** (−3.497)	−0.0004*** (−3.506)	−0.0004*** (−3.753)
Company Size		0.003*** (2.770)				0.006* (1.812)
Analyst			0.009*** (2.965)			0.007** (2.128)
Illiquidity				0.005 (0.144)		0.023 (0.554)
Momentum					0.005 (0.845)	0.003 (0.581)
Short-term Rev.						0.068*** (2.722)
Dividend Yield						−0.00005 (−0.776)
Price to Book						0.0003 (1.359)
Price to Earnings						−0.000 (−0.0001)
Book Value						−0.006 (−1.443)
Constant	−0.047*** (−7.266)	−0.069*** (−5.740)	−0.053*** (−7.171)	−0.047*** (−6.936)	−0.046*** (−7.386)	−0.018 (−0.609)
Region dummy	✓	✓	✓	✓	✓	✓
Industry dummy	✓	✓	✓	✓	✓	✓
Observations	750	750	750	750	750	750
R ²	0.309	0.320	0.319	0.309	0.310	0.340
Adjusted R ²	0.248	0.258	0.257	0.247	0.248	0.272

Note: *t*-statistics are reported in parentheses

*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression results – AR[0] continued

Specifications where the dependent variable is the event-day abnormal return – AR[0]. Columns show the different specifications where the Base model includes the Ukraine-Russia market impact variable (*URSE*), as well as Region and Industry categories. Further models introduce variables to the model one-by-one: Company Size, Analyst Coverage, Illiquidity, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value. Individual coefficients for categories of Regions and Industry are not displayed. The number of observations is the same for all models. T-statistics are reported in brackets below the coefficients. We used White heteroskedasticity-robust standard errors of type 'HC1' (White, 1980).

<i>Dependent variable: AR[0]</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
URSE	−0.0004*** (−3.822)	−0.0004*** (−3.481)	−0.0004*** (−3.685)	−0.0004*** (−3.519)	−0.0003*** (−3.096)	−0.0004*** (−3.753)
Company Size						0.006* (1.812)
Analyst						0.007** (2.128)
Illiquidity						0.023 (0.554)
Momentum						0.003 (0.581)
Short-term Rev.	0.069*** (2.856)					0.068*** (2.722)
Dividend Yield		−0.0001 (−0.859)				−0.00005 (−0.776)
Price to Book			0.0005** (2.226)			0.0003 (1.359)
Price to Earnings				0.00003 (0.714)		−0.000 (−0.0001)
Book Value					0.003** (2.002)	−0.006 (−1.443)
Constant	−0.046*** (−7.126)	−0.047*** (−7.233)	−0.047*** (−7.275)	−0.048*** (−7.088)	−0.081*** (−4.289)	−0.018 (−0.609)
Region dummy	✓	✓	✓	✓	✓	✓
Industry dummy	✓	✓	✓	✓	✓	✓
Observations	750	750	750	750	750	750
R ²	0.320	0.310	0.313	0.310	0.314	0.340
Adjusted R ²	0.259	0.247	0.251	0.248	0.252	0.272

Note: *t*-statistics are reported in parentheses

*p<0.1; **p<0.05; ***p<0.01

6 Conclusions

In this paper, we analyzed the abnormal returns of firms in the global food industry caused by the outbreak of the Russia-Ukraine war in February, 2022. The results are in line with both our hypotheses: 1) the aggregated abnormal returns are negative and significant for all three sectors and nearly all regions (for the event date at least) and 2) the spillover effect from the Ukrainian and Russian market is a significant determinant of abnormal returns with a negative coefficient in the cross-sectional firm-level regressions. The spillover effect remains significant after controlling for financial variables, which by themselves seem to have driven the abnormal returns on the lower and upper end of the distribution. Overall, the variables used in the cross-sectional analysis provide a good fit on event-day abnormal returns.

The motivation behind the analysis is the globally high food inflation observed throughout 2022. Firms within the food industry can represent a large part of the supply chains that begin at the food producer level and span through multiple level of retailers. Furthermore, there is even interconnectedness between producers, when the output of one producer is used as input in the making of another food product. Think of the global maize and wheat dependency on Ukraine and Russia, which perfectly illustrates that relationship. This structure supports our choice of the three sectors. In light of the results, we can say that all three sectors were severely impacted by the war. Also, regional impacts could be compared, which showed that the most affected region is Europe & Central Asia, as one would expect. The fact that the spillover effects from Ukraine and Russia are significant determinants of the abnormal returns shows the importance of the interconnectedness within the food industry.

Based on our results, a possible direction for further research is investment strategies. A factor-based strategy could be constructed which, besides other frequently used variables – industry, country, momentum or financial data – employs spillover effects as well. This is applicable for the same Ukraine and Russia market impact in the future, especially if the conflict is prolonged, or possibly other spillover effects. A long/short strategy (see [Jacobs & Levy, 1993](#)) could be used in which we hold long positions for firms at the last decile of the spillover effects (the lowest values) and we short companies at the first decile (the highest values).

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Appendix

Table A1: Regression results – CAR[−3, 3]

Specifications where the dependent variable is the [−3, 3] cumulative abnormal return. Columns show the different specifications where the Base model includes the Ukraine-Russia market impact variable (*URSE*), as well as Region and Industry categories. Further models introduce variables to the model one-by-one: Company Size, Analyst Coverage, Illiquidity, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value. Individual coefficients for categories of Regions and Industry are not displayed. The number of observations is the same for all models. T-statistics are reported in brackets below the coefficients. We used White heteroskedasticity-robust standard errors of type 'HC1' (White, 1980).

The structure is the same as Table 5. The URSE variable is significant in all specifications, but none of the other variables are significant in the simple models, except Short-term Reversal. In the full model, Company Size and Book Value are also significant. These models show lower *adj.R*² values than the AR[0] specifications.

<i>Dependent variable: CAR[−3, 3]</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
URSE	−0.0005** t = −2.261	−0.0005** t = −2.377	−0.0005** t = −2.277	−0.0005** t = −2.266	−0.0005** t = −2.226	−0.001*** t = −3.736
Company Size		−0.001 t = −0.266				0.010** t = 2.027
Analyst			0.00001 t = 0.002			0.001 t = 0.224
Illiquidity				0.036 t = 1.207		0.040 t = 1.190
Momentum					−0.011 t = −1.192	−0.011 t = −1.295
Short-term Rev.						0.342*** t = 7.459
Dividend Yield						−0.0001 t = −0.374
Price to Book						0.0002 t = 0.880
Price to Earnings						0.00003 t = 0.445
Book Value						−0.015*** t = −2.681
Constant	−0.070*** t = −6.488	−0.067*** t = −3.721	−0.070*** t = −5.769	−0.071*** t = −6.357	−0.072*** t = −6.567	0.067 t = 1.522
Region dummy	✓	✓	✓	✓	✓	✓
Industry dummy	✓	✓	✓	✓	✓	✓
Observations	750	750	750	750	750	750
R ²	0.223	0.223	0.223	0.223	0.224	0.320
Adjusted R ²	0.154	0.153	0.153	0.153	0.154	0.250

Note: t-statistics are reported in parentheses

*p<0.1; **p<0.05; ***p<0.01

Table A1: Regression results – CAR[−3, 3] continued

Specifications where the dependent variable is the [−3, 3] cumulative abnormal return. Columns show the different specifications where the Base model includes the Ukraine-Russia market impact variable (*URSE*), as well as Region and Industry categories. Further models introduce variables to the model one-by-one: Company Size, Analyst Coverage, Illiquidity, Momentum, Short-term Reversal, Dividend Yield, Price to Book, Price to Earnings and Book Value. Individual coefficients for categories of Regions and Industry are not displayed. The number of observations is the same for all models. T-statistics are reported in brackets below the coefficients. We used White heteroskedasticity-robust standard errors of type 'HC1' (White, 1980).

The structure is the same as Table 5. The URSE variable is significant in all specifications, but none of the other variables are significant in the simple models, except Short-term Reversal. In the full model, Company Size and Book Value are also significant. These models show lower *adj.R*² values than the AR[0] specifications.

	<i>Dependent variable: CAR[−3, 3]</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
URSE	−0.001*** t = −3.171	−0.0005** t = −2.241	−0.001** t = −2.362	−0.0005** t = −2.338	−0.001** t = −2.516	−0.001*** t = −3.736
Company Size						0.010** t = 2.027
Analyst						0.001 t = 0.224
Illiquidity						0.040 t = 1.190
Momentum						−0.011 t = −1.295
Short-term Rev.	0.325*** t = 7.309					0.342*** t = 7.459
Dividend Yield		−0.0001 t = −0.478				−0.0001 t = −0.374
Price to Book			0.001 t = 1.570			0.0002 t = 0.880
Price to Earnings				0.0001 t = 1.314		0.00003 t = 0.445
Book Value					−0.003 t = −1.139	−0.015*** t = −2.681
Constant	−0.063*** t = −6.172	−0.070*** t = −6.470	−0.070*** t = −6.486	−0.073*** t = −6.570	−0.036 t = −1.134	0.067 t = 1.522
Region dummy	✓	✓	✓	✓	✓	✓
Industry dummy	✓	✓	✓	✓	✓	✓
Observations	750	750	750	750	750	750
R ²	0.305	0.223	0.225	0.226	0.225	0.320
Adjusted R ²	0.242	0.153	0.155	0.156	0.155	0.250

Note: t-statistics are reported in parentheses

*p<0.1; **p<0.05; ***p<0.01