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Article

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Do industries lead the stock market? Evidence from an emerging stock market[☆]

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ABSTRACT

Examining the gradual information diffusion hypothesis of Hong et al. (2007) in an emerging market context, we show that industry returns possess predictive information regarding the direction of the aggregate stock market in Borsa Istanbul, both in- and out-of-sample, and that the predictive power of industries is often magnified by crisis conditions. Several industries, including basic materials and consumer staples, have out-of-sample predictive power over the aggregate market, although out-of-sample predictability cannot be exploited to extract economic gains based on the direction of industry returns. Industry information emanating from the US stock market has significant spillover effects on Turkish industry returns, creating an opening for industry investment strategies for local investors. We show that foreign participation in the stock market facilitates the diffusion of information from US industries to Turkish industries and that the economic benefits from spillover effects can be as high as 60 percent on annual basis.

1. Introduction

An important implication of the efficient market hypothesis (EMH) is that market prices fully reflect all available information, leaving no room for predictability in stock market fluctuations (Fama, 1991). However, evidence suggests that investors often display inefficiencies in the way they process information, which eventually hinders information discovery through the market pricing process. An established strand in the finance literature argues that information often spreads with a delay (Hong & Stein, 1999), as many investors have limited information-processing capacity and may not pay attention to or cannot extract relevant information from prices (Allen & Gale, 1994; Sims, 2006). In a theoretical challenge to the EMH, Hong et al. (2007) propose the gradual diffusion of information hypothesis and argue that public information is frequently incorporated only partially into asset prices. This occurs because market participants who specialize in trading the broad market index may lag in receiving industry-level information that is already available to investors that specialize in specific industries. This, in turn, paves the way to a predictive relationship between industry returns and the overall stock market, as the information

contained in industry returns spreads slowly across the market.

The main contribution of our study is that, unlike other works in this stream of literature that focus on developed markets, we extend the discussion to an emerging market context and explore the economic implications of a possible predictive relationship between industries and the broad market index. This is an important consideration, as predictability is of great interest to active investors and fund managers who time their investment depending on the direction of the market.

The seminal work by Hong et al. (2007) using US stock returns shows that a significant number of industries, including commercial real estate, metals, petroleum, retail and services, have predictive power over stock market returns. In a later study, however, Hong et al. (2014) report conflicting evidence regarding the predictive content of industry returns, and Tse (2015) presents contrary evidence in which return predictability runs from the stock market to industries. However, using random forests, Ciner (2019) shows that industry returns contain significant out-of-sample forecasting power over the aggregate market index. This finding is confirmed by Tsuji (2012), who demonstrates that US industry portfolios can predict the returns and volatility of Fama and French size (SMB) and value (HML) factors. This implies that

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information spreads gradually in equity markets, as investors cannot quickly extract the profitable information embedded within industry returns. In the emerging market context, Zhang et al. (2022) analyze Chinese data and show that the returns for some industries—in particular, banking and real estate—predict not only market returns and returns for other industries but also growth in industrial output. In their study on 10 Eastern and Southern Asian markets, Lee et al. (2013) show that finance and consumer service industry returns have significant power in explaining movement in market returns and that exchange rates and interest rates are important in explaining the industry–market nexus. However, these papers mostly ignore out-of-sample predictive analysis in their tests, which is crucial from an investment perspective, and the associated economic implications.

We contribute to this literature in several respects. First, we examine the gradual diffusion of information hypothesis by Hong et al. (2007) by analyzing the bidirectional predictive relationship between industry returns and the aggregate stock market in an emerging stock market context, namely, Borsa Istanbul (BIST). Although this strand of the literature has largely overlooked emerging markets, the Turkish stock market in particular has several unique features that make it interesting to study in the context of the information diffusion theory. First, BIST is largely dominated by foreign investors, who held over 60 percent of the shares before the COVID-19 pandemic, and 31 percent of the variation in the aggregate market index fluctuations is explained by foreign investors' trades (Coskun et al., 2023). Second, as noted by Ciner and Karagozoglu (2008), significant information asymmetry is found between foreign and domestic investors, in which foreign investors have informational advantages over their domestic counterparts, and this, in turn, can hinder efficient diffusion of market information across all market participants. This inefficiency in the spread of information can be magnified because of the short-term considerations of investors in the market who respond to market information in a myopic fashion (Cetin, 2021).

Another interesting characteristic of the Turkish stock market is that firms listed on BIST must first disclose their announcements on the Public Disclosure Platform (PDP), whereas, in most other stock markets, public firms can disclose their announcements in multiple ways, such as press releases and social media. This requirement enables all market participants to access complete firm-level information over the internet at the same time and at no cost. So, this characteristic, coupled with high volatility and geopolitical uncertainty experienced by investors (Boyukaslan et al., 2024), makes the Turkish stock market an interesting platform for testing the gradual diffusion of information hypothesis.

The second contribution of our study is in exploring the role of market crises in the diffusion of information between industries and the aggregate market. In particular, we examine whether local and global crises magnify the diffusion of information from certain industries. The identification of industries with predictive ability under various market conditions is especially important in light of the COVID-19 pandemic, which showed the leading role of certain industries in the real economy (Niu et al., 2024).

Third, unlike other works in this strand of the literature, we extend our tests to examine the out-of-sample predictability relationships, as in-sample predictability does not necessarily guarantee out-of-sample predictive performance. Fourth, motivated by the evidence in Monteiro et al. (2023) that the returns of US industries significantly Granger cause the returns of most other countries' industries, we examine the predictive role of US industry returns over local industry returns in Türkiye. Finally, and more importantly, we extend our analysis to the economic implications of the predictive power of industries over aggregate market returns. To the best of our knowledge, our study is the first to perform such a comprehensive evaluation of the gradual diffusion of information hypothesis in an emerging market context.

Our findings yield significant evidence of predictability in aggregate market returns using industry returns. While travel and leisure is the only industry that possesses predictive ability over the aggregate market

during the sample period, we show that the predictive role of several industries via information diffusion from these industries to the rest of the market is magnified in crisis periods. We also show that the in-sample predictive power of industries extends to the out-sample as well, and several industries—including basic materials, consumer staples, and household goods and home construction—have out-of-sample predictive power over the aggregate market. However, this out-of-sample predictive ability cannot be exploited to extract economic gains by investing in the market index based on the direction of industry returns in the previous month. Finally, and more interestingly, we find that US industry returns have greater predictive power over industry returns in Türkiye than the local industry returns. Consistent with the evidence in Monteiro et al. (2023), we find that local industry returns have a delayed response to new information emanating from US industries, in particular, financials. Moreover, this predictive relationship yields economic benefits as high as 60 percent on annual basis by conditioning industry investment on signals from US financials.

The remainder of the paper is structured as follows. Section 2 presents the data and methodology. Section 3 discusses the in- and out-of-sample predictability tests and the economic analysis. Section 4 concludes, with directions for future research.

2. Methodology and data

2.1. Data

Our dataset includes monthly Datastream indexes for 16 Turkish industries and the aggregate stock market index for BIST over the period January 1995 to March 2022, obtained from Datastream. These industry indexes are market value-weighted indexes created by Datastream, which classifies stocks into industries based on their SIC codes.¹ Based on the common starting date for the industry indexes available, the industries in our sample are basic materials, beverages, chemicals, construction, consumer discretionary, consumer staples, energy, financials, food producers, glass, household goods and home construction, industrials, industrial metals and mining, telecommunications, media and IT, travel and leisure and utilities. Moreover, monthly Datastream indexes for three US industries—basic materials, energy, and financials—are also collected to test the predictive power of US industries. Finally, monthly Turkish industrial production index data is obtained from Federal Reserve Economic Data. Excess returns are calculated using the interbank rate as the risk-free rate.

Table 1 presents the descriptive statistics for monthly excess returns. Thanks to the rapid growth in the construction industry in Türkiye during much of the sample period, we observe the highest excess returns for construction (0.5%), while telecommunications, media and IT has the lowest excess returns, possibly because of the high taxes imposed on this sector, restraining growth in the mobile sector and its resulting economic benefits. Food producers, however, have the highest volatility in monthly returns (19.2%), followed by chemicals and travel and leisure. The high volatility in these industries—in particular, food producers and travel and leisure—could be due to the COVID-19 pandemic, which led to excessive demand pressure for food products as a result of prolonged lockdowns globally. The travel and leisure industry certainly had its fair share of volatility during this period, as this industry is vulnerable to global crises (Pforr & Hosie, 2008), security problems, economic crises, and health problems because of its postponable structure (Blake & Sinclair, 2003). This observation is in line with the evidence on the international hospitality industry (Nicola et al., 2020). The correlation estimates indicate a high degree of correlation between industry returns and the aggregate market index, in which financials and consumer discretionary have the highest correlations (0.939 and 0.904,

¹ For further details, see <https://www.scribd.com/document/59476431/Data-Stream-Global-Equity-Manual/>.

Table 1
Summary statistics.

	Mean	Std. Dev.	Correlation	MV	Turnover
Raw materials	0.000	0.127	0.816	28,277.90	11.869
Beverages	−0.005	0.114	0.656	12,485.80	92.962
Chemicals	0.002	0.171	0.613	8259.30	0.629
Construction	0.005	0.145	0.671	13,686.60	7.413
Consumer discretionary	−0.004	0.129	0.904	37,435.70	46.357
Consumer staples	−0.006	0.123	0.887	44,222.60	37.975
Energy	−0.006	0.133	0.815	25,096.30	7.084
Financials	−0.005	0.134	0.939	133,167.70	92.518
Food producers	0.001	0.192	0.337	8154.20	0.053
Glass	−0.002	0.140	0.815	6058.60	6.005
Hh. Goods & home constr.	−0.002	0.141	0.850	9840.10	94.513
Ind. Metal & mining	−0.001	0.143	0.744	16,293.30	55.713
Industrials	−0.005	0.131	0.882	31,316.60	523.249
Telecom, media, & IT	−0.008	0.134	0.827	34,088.30	32.513
Travel & leisure	−0.007	0.168	0.728	7301.30	1.614
Utilities	−0.003	0.130	0.762	4035.40	19.765
Market index	−0.005	0.116	–	–	–

Note: This table presents the descriptive statistics for monthly industry and aggregate market excess returns for the sample period from January 1995 to March 2022. Correlation denotes the correlation between industry and aggregate market index returns. MV and Turnover indicate monthly average figures for market capitalization in millions of Turkish lira and the percentage of outstanding shares traded during a month, respectively.

respectively). Finally, we observe the highest turnover, measured by the number of shares traded divided by the number of shares outstanding, for the industrials sector followed by household goods and home construction, beverages, and financials, and, among the 16 industries considered in the sample, Financials have the largest market capitalization.²

2.2. Methodology

The following pairwise Granger-causality regressions, our benchmark predictive model, are performed between monthly excess returns for industry i (R_{it}) and the excess market returns (R_{mt}) formulated as

$$R_{mt} = \alpha_{1,i} + \alpha_{2,i}R_{i,t-1} + \alpha_{3,i}R_{m,t-1} + \alpha_{4,i}INF_{t-1} + \alpha_{5,i}MVOL_{t-1} + \varepsilon_{1,it} \quad (1)$$

$$R_{it} = \beta_{1,i} + \beta_{2,i}R_{i,t-1} + \beta_{3,i}R_{m,t-1} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \varepsilon_{2,it} \quad (2)$$

where INF is monthly inflation and $MVOL$ is market volatility, both used as control variables in line with Hong et al. (2007) and Zhang et al. (2022) for the US and Chinese stock markets, respectively, so that we have a basis for comparing our findings with theirs.³ Market volatility is calculated as the volatility of daily market index returns for the month. In Equation (1), the coefficient $\alpha_{2,i}$ captures predictability from one-month lagged industry index returns to the aggregate market index, and $\beta_{3,i}$ in Equation (2) gives the predictive power of lagged market

² To provide further insight into the differences among industry indexes, we also examine the sensitivity of industry returns to the Fama-French market, size, and value factors. Several industries—e.g., chemicals, glass, household goods and home construction and utilities—have significantly positive sensitivities to the size factor, whereas six industries have significantly positive sensitivity to the book-to-market factor, implying the presence of certain firm characteristics in these industries.

³ We have also estimated the models in an alternative specification using Fama-French SMB and HML factors as well as the Amihud (2002) illiquidity measure as additional control variables. The results are consistent with those in the original specification and are available from the author upon request.

index returns over industry index returns. Although the seminal work by Hong et al. (2007) does not consider causality from the market to industries, in a later study, Tse (2015) documents such evidence for certain US industries. Given this, our benchmark model examines predictability in both directions to offer insights into possible bidirectional causal linkages between industry and the broad market index returns.

2.3. The impact of local and global crises on the lead-lag relationship

Recent evidence shows that the predictive role of industries over the aggregate market can be time varying (Niu et al., 2024) and that some industries can play a more dominant leading role in crisis periods. In this context, Guerrieri et al. (2022), using the Keynesian supply shock theory, suggest that a shock to potential output in some sectors of the economy can spill over into inefficient demand shock in other sectors, driving aggregate economic activity below its potential level. Similarly, focusing on the period of the COVID-19 pandemic, Tan et al. (2022) show that companies and activities associated with transportation and services are the most significantly impacted, whereas companies and supply chains related to manufacturing lead in economic losses. Clearly, this interplay in industry-level information during periods of market stress can be further strengthened via the so-called information hierarchies that exists even among informed traders (Xue & Gencay, 2012), reducing the rate of information diffusion and informational efficiency. Accordingly, we use the following model to capture the possible role of crises in the lead-lag relationship between industries and the aggregate market:

$$R_{mt} = \alpha_{1,i} + \alpha_{2,i}R_{i,t-1} + \alpha_{3,i}R_{m,t-1} + \alpha_{4,i}INF_{t-1} + \alpha_{5,i}MVOL_{t-1} + \alpha_{6,i}D_t + \alpha_{7,i}(D_t \times R_{i,t-1}) + \alpha_{8,i}(D_t \times R_{m,t-1}) + \varepsilon_{1,it} \quad (3)$$

$$R_{it} = \beta_{1,i} + \beta_{2,i}R_{i,t-1} + \beta_{3,i}R_{m,t-1} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \beta_{6,i}D_t + \beta_{7,i}(D_t \times R_{i,t-1}) + \beta_{8,i}(D_t \times R_{m,t-1}) + \varepsilon_{2,it} \quad (4)$$

Using this model, we first follow Comert and Yeldan (2018) and consider three major local crises for Turkish financial markets—including the periods January–March 1995 (aftermath of the 1994 financial crisis), August 1999 (earthquake), and November 2000–October 2001 (banking crisis)—represented by the dummy variable D_t . In this formulation, $\alpha_{2,i}$ and $\beta_{2,i}$ measure predictability in non-crisis periods, whereas $\alpha_{2,i} + \alpha_{7,i}$ and $\beta_{2,i} + \beta_{7,i}$ capture the predictive effects during periods of crisis. Separately, we also examine the role of global crises on the lead-lag relationship between industries and the aggregate market by creating dummy variables for the 2008 global financial crisis (GFC, August 2007–September 2009) as per Comert and Yeldan (2018), and the COVID-19 pandemic (December 2019–June 2020) as per Danisman et al. (2021) and Zamfir and Iordache (2022).

2.4. The predictive power of leading industries

Clearly, predictive relationships can have significant investment implications, as our findings suggest that investors can use signals from particular industries to take investment positions in the stock market index. This could also imply the potential for market timing in certain industries, conditional on price movement in leading industries. Indeed, Ellington et al. (2022) show that in the Chinese stock market, oil, telecommunications, and financial industry portfolio returns are significant predictors of other industries. Zhang et al. (2022) identify industries in the Chinese stock market that have predictive power over the broad stock market index and use them as predictors of other industries. Following Zhang et al. (2022), we offer further insight about this argument by examining the predictive power of each leading industry over the 15 other industries as follows:

$$R_{it} = \beta_{1,i} + \beta_{2,i}R_{i,t-1} + \beta_{3,i}R_{j,t-1}^{\text{leading}} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \varepsilon_{it} \quad (5)$$

where $R_{j,t-1}^{\text{leading}}$ is the lagged excess return on leading industry j in month $t-1$. Clearly, a significant estimate for $\beta_{3,i}$ suggests the presence of significant information spillovers from industry j to industry i .

2.5. Out-of-sample predictive analysis

In-sample predictive relationships do not guarantee that the predictive power of an industry extends to an out-of-sample setting, which might have significant investment implications, as noted by Welch and Goyal (2008). Accordingly, to test the out-of-sample predictive performance of industries over the aggregate market, we follow Zhang et al. (2022) and examine the out-of-sample forecasts by comparing the mean squared prediction errors (MSPEs) for null and alternative models. The restricted (parsimonious) model used to test the null hypothesis of predictability from each industry to the market is a modified version of Equation (1), which omits $R_{i,t-1}$.

$$R_{m,t} = \alpha_{1,i} + \alpha_{3,i}R_{m,t-1} + \alpha_{4,i}INF_{t-1} + \alpha_{5,i}MVOL_{t-1} + \varepsilon_{1,it} \quad (6)$$

while the alternative (unrestricted) model is in Equation (1). Similarly, the restricted model used in the null hypothesis of predictability from the market to industry is a modified version of Equation (2), which omits $R_{m,t-1}$:

$$R_{i,t} = \beta_{1,i} + \beta_{2,i}R_{i,t-1} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \varepsilon_{2,it} \quad (7)$$

while the corresponding alternative model is in Equation (2). Clark and West (2007) state that, if the null and alternative forecasting models are nested, as they are here, the alternative model introduces sampling error into the forecasting process that will inflate its MSPE. They suggest using a t -statistic, denoted $ENC-t$ (encompassing test statistic), which adjusts the MSPE to account for this sampling error and tests the difference in MSPE between the null and alternative models. Following their suggestion, we draw conclusions based on $ENC-t$. Note that, in our analysis, we use the first half of the sample in the initial estimation, and the second half for out-of-sample prediction, as we generated one-step-ahead forecasts via rolling regressions.

2.6. The predictive role of US industries

Monteiro et al. (2023) analyze the lead-lag relationships between US industry indexes and those of six other major countries and show that the weekly returns of US industries, particularly basic materials and energy, significantly Granger cause the returns of most other countries' industries. Clearly, if local industry returns have a delayed response to the new information from US industries, this could create industry investment strategies for local investors conditional on US industry return dynamics. Our motivation to examine the predictive effect of US-based economic information over financial markets in Türkiye is supported by several studies. For example, Ekinici et al. (2019) show that US macroeconomic news releases have a significant volatility effect on stock returns in Türkiye, whereas Berument & Ince (2005) show that the S&P 500 affects Turkish stock market returns with current and lagged values but not vice versa. Later, Özdemir and Vurur (2019) document unidirectional causality from the S&P 500 index to the BIST 100. Against this backdrop, in order to explore possible linkages to US industries, we once again estimate Equation (5), in which $R_{j,t-1}^{\text{leading}}$ is the lagged excess return in leading US industry j in month $t-1$. A significant estimate for $\beta_{3,i}$ would suggest the presence of significant information spillovers from US industry j to Turkish industry i . In addition to this in-sample analysis, we also explore the out-of-sample predictive performance of leading US industries over the 16 Turkish industries.

3. Empirical results

3.1. The predictive power of industries over the stock market

One of the characteristics of our sample that makes it particularly interesting in the context of the gradual information diffusion hypothesis is the establishment of the PDP by the Capital Markets Board of Türkiye in 2009. Firms that trade on BIST are required first to disclose their announcements through the centralized PDP system. To examine whether the establishment of this platform, which regulates the dissemination of information from a single source, has any impact, we perform our predictive analysis with the full sample as well as with subsamples for before and after the creation of the PDP.⁴

Table 2 presents the results of the pairwise Granger-causality regressions for the 16 industry returns ($R_{i,t}$) and the market ($R_{m,t}$) using Equations (1) and (2), controlling for the inflation rate and market volatility. The columns IND $\rightarrow$ MKT report $\alpha_{2,i}$ in Equation (1), while the columns MKT $\rightarrow$ IND report $\beta_{3,i}$ in Equation (2). The corresponding t -statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors are reported in the column next to each estimate. Panels A, B, and C give the findings for the full, pre-PDP, and post-PDP samples, respectively. Panel A gives the direction of predictability from industries to the aggregate market index, showing that the only industry with predictive ability over the aggregate market is travel and leisure, with an estimated coefficient of -0.118 . This is not unexpected, considering that in 2018 10 percent of the gross national product and 10 percent of employment in Türkiye came from tourism (COMCEC, 2019).⁵ This finding is consistent with those that establish a direct link between tourism and economic growth in Türkiye, such as Gunduz and Hatemi (2005), Bozkurt (2019), Samimi et al. (2011), Bozgeyik and Yologlu (2015), Ohlan (2017), Fareed et al. (2018), and Ayaydin et al. (2019). The findings for Equation (2), however, yield no consistent evidence of predictability from the market index to industry returns, suggesting that investors who focus on trading industry indexes do not necessarily experience delays in receiving market-level information that is already available to traders of the broad market index.

However, the findings in Panels B and C for the pre- and post-PDP periods show that the predictive power of the travel and leisure industry is largely limited to the pre-PDP period, whereas construction plays a dominant leading role for the aggregate market index during the post-PDP period. The decline in the predictive power of travel and leisure during the post-PDP period might be due to the inclusion of the COVID-19 pandemic as well as the downing of a Russian airplane in November 2015, which led to a sharp decline in tourism revenue during much of this subperiod. However, in Türkiye the construction industry experienced a remarkable boom in 2010–2017, when the average annual sectoral growth rate was 9 percent. Construction has a prominent position globally.⁶ Accordingly, the predictive power of this industry might be a manifestation of its remarkable growth in this period, which has been a driver of the overall economy.

Nevertheless, our findings show that the establishment of the PDP did not lead to a notable structural change in the lead-lag relationship between industry returns and the aggregate market index. The only striking difference is that, since the establishment of the PDP, the aggregate market has played a leading role in several industries.

⁴ Although the PDP was established in 2009, it went into effect on January 1, 2010, so we use this date as the cut-off date for our pre- and post-PDP subsamples.

⁵ Standing Committee for Economic and Commercial Cooperation of the Organization of Islamic Cooperation.

⁶ In 2016, the Top 250 International Contractors List compiled by the Engineering News-Record included a total of 39 Turkish construction and contracting companies (<https://www.enr.com/toplists/2016-Top-250-International-Contractors1/>).

Table 2

Predictive regressions between industry and market returns.

	Panel A: Full sample				Panel B: Pre-PDP				Panel C: Post-PDP			
	IND → MKT		MKT → IND		IND → MKT		MKT → IND		IND → MKT		MKT → IND	
	IND(-1)	t-stat	MKT(-1)	t-stat	IND(-1)	t-stat	MKT(-1)	t-stat	IND(-1)	t-stat	MKT(-1)	t-stat
Raw materials	0.0985	1.153	−0.043	0.374	0.133	1.139	−0.078	0.510	0.045	0.514	0.157	1.400
Beverages	0.144	1.289	0.090	1.050	0.217	1.482	0.057	0.552	−0.118	1.194	0.327***	2.852
Chemicals	0.048	1.166	−0.124	0.841	0.056	1.278	−0.194	1.156	−0.003	0.038	0.353**	2.166
Construction	0.014	0.194	−0.083	0.767	0.052	0.577	−0.122	0.914	−0.160**	2.424	0.079	0.752
Consumer discretionary	−0.103	0.716	0.000	0.001	−0.104	0.506	−0.087	0.395	−0.038	0.244	0.218	0.906
Consumer staples	0.061	0.362	−0.102	0.654	0.103	0.344	−0.227	0.849	−0.049	0.579	0.275***	2.717
Energy	−0.063	0.734	−0.021	0.174	−0.064	0.627	−0.013	0.094	0.008	0.077	0.014	0.098
Financials	0.025	0.179	0.035	0.173	0.003	0.014	0.121	0.480	0.074	0.518	−0.217	0.706
Food producers	0.017	0.506	0.173	1.517	0.008	0.137	0.123	0.915	0.015	0.563	0.565**	2.013
Glass	−0.035	0.363	0.137	0.859	−0.015	0.108	0.096	0.472	−0.090	1.336	0.263	1.371
Hh. goods & home constr.	0.021	0.199	−0.005	0.031	−0.001	0.005	−0.058	0.272	0.128	1.270	0.154	1.058
Ind. Metal & mining	0.050	0.683	−0.159	1.348	0.047	0.335	−0.085	0.506	−0.092	0.898	0.071	0.640
Industrials	0.002	0.024	−0.054	0.465	0.059	0.547	−0.232	1.471	0.035	0.573	0.152	1.218
Telecom, media, & IT	0.074	0.557	−0.164	1.029	0.110	0.686	−0.252	1.296	−0.114	0.796	0.258*	1.781
Travel & leisure	−0.118**	2.080	−0.100	0.679	−0.148*	1.991	−0.076	0.413	−0.022	0.307	−0.014	0.076
Utilities	−0.001	0.013	0.014	0.114	0.032	0.236	−0.060	0.373	−0.069	1.040	0.240*	1.820

Note: This table presents the results of the pairwise Granger-causality regressions between industry ($R_{i,t}$) and the market excess returns ($R_{m,t}$) shown in Equations (1) and (2). The columns IND → MKT report $\alpha_{2,i}$ in Equation (1), while the columns MKT → IND report $\beta_{3,i}$ in Equation (2). The corresponding t -statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors are reported in the column next to each estimate. Panels A, B, and C report the findings for the full, pre-, and post-Public Disclosure Platform (PDP) samples, respectively. January 2010 is the beginning of post-PDP period. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively.

Specifically, we observe that the market index captures predictive information for beverages, chemicals, consumer staples, food producers, telecommunications, media and IT and utilities in the post-PDP period. With the exception of Cortuk and Erten (2016), who show that introduction of the PDP led to a drop in aggregate market volatility, no evidence has been presented in the literature regarding the impact of the PDP on the stock market. Presumably, the reverse predictive role of the passive market index for individual industries might indicate that broad market index traders are taking advantage of the informational efficiency created by the PDP platform, which has given all market participants access to complete firm-level information over the internet simultaneously and at no cost.

We next examine the role of crises on the lead-lag relationships based on Equations (3) and (4). Our main interest is again $\alpha_{2,i}$ and $\beta_{2,i}$ estimates that measure the predictability during non-crisis periods, whereas $\alpha_{2,i} + \alpha_{7,i}$ and $\beta_{2,i} + \beta_{7,i}$ capture predictability during crisis periods. The results regarding local crises (shown in Appendix Table A1) indicate that only one industry, travel and leisure, has predictive power in non-crisis periods; hence, the predictive role of travel and leisure over the aggregate market in this empirical specification is robust. Our examination of the significance of $\alpha_{2,i} + \alpha_{7,i}$ shows that basic materials and glass have predictive power only in periods of local crisis.⁷ Moreover, significant predictability in the opposite direction, from the market index to food producers and glass, is found in non-crisis periods.

During the GFC, the predictive role of travel and leisure over the aggregate market persists (in Appendix Table A2), but it is again limited to non-crisis periods. Moreover, beverages also play a significant predictive role in both crisis and non-crisis periods. But consumer discretionary, food producers, household goods and home construction, and telecommunications, media, and IT have significant predictive power only during the period of global crisis. When we consider predictability in the opposite direction, however, we observe that the market index has no predictive power over any of the 16 industries in non-crisis periods.

During the nonpandemic period, only travel and leisure plays a predictive role over the aggregate market (see Appendix Table A3). Several industries (basic materials, beverages, consumer discretionary,

consumer staples, glass, industrials, industrial metals and mining and telecommunications, media and IT) have significant predictive power only during the pandemic period. Moreover, during the nonpandemic period, significant predictability in the opposite direction runs from the market index to energy, industrials, and travel and leisure.

3.1.1. Additional market-specific considerations

Following a suggestion by an anonymous referee to test a hypothesis as to whether potential clustering of initial public offerings (IPOs) in certain industries creates any bias in industry comparisons, we formed a sample of IPOs realized per year during the study period and created a dummy variable for the years in which the number of IPOs exceeds the median over that period. The results of this test show that IPO activity does not have a significant impact on the predictive power of Turkish industries on the aggregate market. A similar observation is made on the predictive power of aggregate market on Turkish industries with the exception of food producers and utilities.

We also test the impact of two notable changes in the Turkish economy on the lead-lag relationships between industries and the aggregate market. First, we examine the role of foreign ownership in the BIST. Unfortunately, monthly data on foreign ownership do not go back to 1995, the beginning of our sample period. Therefore, we employ an alternative approach, following Choi and Havel (2023), who indicate that foreign ownership falls during periods of high geopolitical risk (GPR), and use monthly geopolitical risk data for Türkiye as a proxy.⁸ Using the GPR index, we generate a monthly dummy variable that takes on the value of one for the months during which the GPR index exceeds its median value over the sample period and zero otherwise. Our results show that foreign ownership has only a minor impact on the predictive relationship between the aggregate market and Turkish industries. Only one industry, consumer discretionary, plays a significant predictive role over the aggregate market during periods of low foreign ownership.

We next examine the potential impact of a decline in real interest rates in Türkiye. For that purpose, we construct a monthly dummy variable that takes on the value of one for the months during which the real interest rate falls below the 30th percentile of the distribution of real rates and zero otherwise. We find that the fall in real interest rates has a

⁷ For the sake of brevity, the statistical significance of $\alpha_{2,i} + \alpha_{7,i}$ and $\beta_{2,i} + \beta_{7,i}$ are not reported in Appendix Tables A1–A3. They are available from the authors upon request.

⁸ <https://www.matteoiacoviello.com/gpr.htm>. The construction of the geopolitical risk index is discussed in Caldara and Iacoviello (2022).

minor impact on the predictive relationship between the aggregate market and Turkish industries. Only one statistically significant estimate, that of food producers, indicates that the aggregate market displays a significant predictive role during periods with high negative real interest rates. However, as discussed in Section 3.5, the impact of foreign ownership primarily enhances the predictive role of US industries over Turkish industries.

In sum, our findings indicate that mainly three industries—travel and leisure, construction, and beverages—play a leading role over the market. When we examine the predictive power of these three leading industries over the remaining 15 industries, as shown in Table 3, we find that travel and leisure has the highest predictive power as it leads six industries, whereas construction leads one industry and beverages lead zero. Overall, our findings identify travel and leisure as a leading industry, with predictive power over both the aggregate market index and industry returns, which is robust to alternative empirical specifications.

3.2. Out-of-sample predictive power of industries over stock market returns

Although the in-sample results presented offer some insight into the predictive relationship between industry returns and the aggregate market, what really matters from a practical investment perspective is whether these predictive relationships help improve out-of-sample forecasts, which would enable investors to construct forward-looking investment strategies (Niu et al., 2024). To do so, we follow Zhang et al. (2022) and examine the accuracy of out-of-sample forecasts by comparing the MSPEs of our null and alternative models (see Section 2.5).

Table 4 presents the MSPEs for the restricted and unrestricted forecasting models as well as the encompassing t -statistics (ENC- t) by Clark and West (2007). The results in the table show that several industries—basic materials, consumer staples, and household goods and home construction—have out-of-sample predictive power over the market, whereas the aggregate market can predict beverages, consumer staples, and food producers out-of-sample. This is important because the out-of-sample predictive relationships can be exploited by active traders for market-timing strategies.

Although it might be surprising that the only industry with a consistent leading role over the market, travel and leisure, does not have out-of-sample predictive power over the market, this result is consistent with our earlier finding that the predictive power of this industry is largely limited to the pre-PDP period.

Table 3
The predictive role of leading domestic industries.

	Travel → IND		Construction → IND		Beverages → IND	
	Travel(-1)	t -stat	Construction(-1)	t -stat	Beverages(-1)	t -stat
Raw materials	−0.090*	1.680	0.037	0.616	0.089	1.017
Beverages	−0.044	0.862	−0.025	0.573	–	–
Chemicals	−0.042	0.554	0.012	0.164	0.048	0.400
Construction	−0.140**	2.005	–	–	−0.007	0.072
Consumer discretionary	−0.097	1.161	−0.029	0.514	0.071	0.857
Consumer staples	−0.124***	2.658	0.003	0.044	0.061	0.779
Energy	−0.102	1.568	−0.057	1.074	−0.057	0.711
Financials	−0.078	1.559	0.012	0.205	0.105	1.182
Food producers	−0.045	0.650	0.146*	1.776	0.162	1.598
Glass	−0.011	0.195	0.043	0.596	0.139	1.313
Hh. goods & home constr.	−0.026	0.412	−0.003	0.050	0.102	1.167
Ind. Metal & mining	−0.112**	2.001	−0.093	1.530	−0.001	0.016
Industrials	−0.112**	2.190	0.023	0.409	0.092	1.174
Telecom, media, & IT	−0.176**	2.480	0.006	0.088	0.027	0.275
Travel & leisure	–	–	−0.081	1.144	−0.010	0.083
Utilities	−0.027	0.373	−0.044	0.657	0.079	0.777

Note: This table reports the results of predictive regressions, shown in Equation (5), that measure the predictive power of three leading domestic industries including travel & leisure (Travel → IND), construction (Construction → IND) and beverages (Beverages → IND) over the remaining 15 industries. The columns Travel(-1), Construction(-1) and Beverages(-1) report $\beta_{3,i}$ in Equation (5) with the corresponding t -statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors reported in the column next to each estimate. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively.

3.3. Return predictability and economic fundamentals

Hong et al. (2007) argue that the ability of industries to predict aggregate stock market returns should be significantly correlated with their ability to forecast economic fundamentals, such as growth in industrial production. Their findings indicate that many industries that are capable of predicting market returns can also predict economic growth. Against this backdrop, to test whether industries have any predictive power over the real economy, following Hong et al. (2007), we investigate the causal relationship between stock returns and economic activity as follows:

$$IOG_t = \beta_{1,i} + \beta_{2,i}R_{it-1} + \beta_{3,i}R_{m,t-1} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \sum_{j=1}^3 IOG_{t-j} + \varepsilon_{it} \quad (8)$$

where IOG_t is the growth rate of industrial output in month t . In this setting, a significant value of $\beta_{2,i}$ would indicate that industry i has predictive power to forecast economic growth.

Table 5 presents the results for the predictive effect of industry returns over the growth rate of industrial output, in which the column IND(-1) gives the estimates for $\beta_{2,i}$ in Equation (8). Consumer staples, food producers, and household goods and home construction demonstrate significant predictive power. Because two of the three industries with out-of-sample predictive power—consumer staples and household goods and home construction—have predictive power over growth in industrial production; these results support Hong et al. (2007). However, travel and leisure, the only industry that consistently plays a leading role over the market based on in-sample analysis does not have this predictive power.

In a related study, Naes et al. (2011) show that, in the US, small and illiquid industries are more informative in leading the market. In addition, Wu and Shamsuddin (2014) show that, in Australia, the ability of an industry to forecast the market is not necessarily related to its propensity to predict economic growth. Rather, they argue that the ability of an industry to lead the market is influenced by proxies for investor attention. More specifically, neglected industries have greater information in leading the market because of delayed investor attention to the information content of these industries. Accordingly, although somewhat confusingly, our findings might be a manifestation of delayed investor recognition of information contained in neglected industries.

Table 4
Out-of-sample forecasting analysis.

	Panel A: IND → MKT			Panel B: MKT → IND		
	Restricted MSE	Unrestricted MSE	ENC- <i>t</i>	Restricted MSE	Unrestricted MSE	ENC- <i>t</i>
Raw materials	0.005	0.005	1.159*	0.008	0.008	−0.724
Beverages	0.005	0.006	0.329	0.006	0.006	1.997**
Chemicals	0.005	0.005	−0.131	0.009	0.010	−0.875
Construction	0.005	0.006	−0.869	0.010	0.010	−0.913
Consumer discretionary	0.005	0.006	−1.421	0.008	0.008	−0.968
Consumer staples	0.005	0.005	1.313*	0.007	0.007	1.244*
Energy	0.005	0.006	−2.035	0.008	0.008	−0.936
Financials	0.005	0.005	−0.440	0.009	0.009	−0.120
Food producers	0.005	0.006	0.360	0.038	0.038	1.161*
Glass	0.005	0.005	−0.783	0.011	0.011	0.600
Hh. goods & home constr.	0.005	0.005	1.055*	0.010	0.010	−0.293
Ind. Metal & mining	0.005	0.005	0.906	0.011	0.011	−0.627
Industrials	0.005	0.005	−0.455	0.008	0.008	−0.785
Telecom, media, & IT	0.005	0.006	−0.421	0.005	0.005	0.282
Travel & leisure	0.005	0.006	−0.755	0.015	0.016	−1.354
Utilities	0.005	0.006	−1.129	0.010	0.010	0.570

Note: This table presents the mean squared prediction error (MSPE) estimates for the restricted and unrestricted forecasting models described in Section 2.5. In Panel A, the restricted (parsimonious) model used in the null hypothesis of predictability from each industry to the market follows Equation (6), while the unrestricted (alternative) model is the model in Equation (1). In Panel B, the restricted model used in the null hypothesis follows Equation (7), while the corresponding alternative model is given by Equation (2). The first half of the sample is used as the initial estimation sample and the second half as the out-of-sample prediction sample as we generated one-step-ahead forecasts via rolling regressions. ENC*t* denotes the encompassing *t*-statistics, which adjust the MSPE to account for the sampling error that leads to upward bias in the MSPE of the unrestricted model. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively based on the critical values provided by Clark and West (2007).

Table 5
The predictive role of industries over economic fundamentals.

	IND(-1)	<i>t</i> -stat
Raw materials	0.015	0.279
Beverages	0.057	0.971
Chemicals	−0.032	1.124
Construction	−0.003	0.085
Consumer discretionary	0.103	1.001
Consumer staples	0.160*	1.710
Energy	−0.064	1.059
Financials	−0.025	0.230
Food producers	0.050**	2.235
Glass	−0.020	0.395
Hh. goods & home constr.	0.107*	1.738
Ind. Metal & mining	0.045	0.903
Industrials	0.032	0.480
Telecom, media, & IT	−0.076	1.535
Travel & leisure	−0.017	0.440
Utilities	−0.013	0.200

Note: This table presents the results on the predictive effect of industry returns over industrial output growth rate as shown in Equation (8) with the column IND (-1) reporting the estimates for $\beta_{2,i}$. The corresponding *t*-statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors are given in the column next to each estimate. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively.

Table 1 shows that the travel and leisure industry has lower trading turnover and market capitalization, confirming the results in prior papers that industries that attract less investor attention are associated with slower diffusion of information to the rest of the market.

3.4. Economic evaluation

To evaluate the out-of-sample economic implications of the predictive relationships between industry and aggregate market index returns, we next explore whether the direction of industry (market index) returns in the prior month can be used to take positions in the market index (industry) in the subsequent month. The results in Panel A (B) in Table 6 give the mean returns on the market index (industry) after positive and negative returns to the industry (market) in the preceding month. For example, in Panel A, the mean return on the market after upward

(downward) movement in basic materials is 0.022 percent (0.030%), and the difference in mean returns (DIF), −0.008 percent, is statistically insignificant. The returns throughout Panel A have largely insignificant differences, suggesting that the signals from industry returns cannot be used to take positions in the market index in the subsequent month in order to obtain economic benefits. Likewise, Panel B shows largely insignificant mean differences in subsequent industry returns after positive and negative market returns, with the exception of glass and utilities, for which DIF is 2.8 percent and 2.2 percent, respectively. This suggests that investors can time their investment in these industries based on the direction of the aggregate market index.

3.5. The predictive power of US industries

As mentioned earlier, prior research has shown that US-based economic information plays a significant role in financial market dynamics in Türkiye (Berument & Ince, 2005; Ekinci et al., 2019; Özdemir & Vurur, 2019), however, they do not explore the role of the US market in the predictive relationships between industry and market returns. We provide evidence on this issue by testing unidirectional causality running from US industries to each of the 16 industries using Equation (5). Following Monteiro et al. (2023), we examine the leading role of US basic materials and US energy. We also consider US financials based on the evidence of cross-industry linkages, which suggests that the lagged returns of the financial and commodity-related industries can be used to forecast most other industries (e.g., Rapach et al., 2019). Table 7 estimates $\beta_{3,i}$ for each Turkish industry in our sample.

Table 7 shows that the effect of US energy on Turkish industry returns is insignificant. However, consistent with Monteiro et al. (2023), we find that US basic materials leads some Turkish industries, including beverages, construction, and industrials. More strikingly, there is evidence that US financials leads a large number of Turkish industries including construction, consumer discretionary, consumer staples, household goods and home construction, industrials, travel and leisure and utilities, suggesting that Turkish industries react with some delay to new information emanating from the US.

We next examine the predictive role of these three US industries separately in the periods before and after the global finance crisis. Appendix Table A4 presents the results. In Panel A, US basic materials and US energy play no predictive role before the GFC, and US financials

Table 6
Economic implications of predictability from domestic industries.

	Panel A: IND → MKT					Panel B: MKT → IND				
	Positive		Negative		DIF	Positive		Negative		DIF
	Mean	Stdev	Mean	Stdev		Mean	Stdev	Mean	Stdev	
Raw materials	0.022	0.128	0.030	0.122	−0.008	0.022	0.112	0.019	0.119	0.003
Beverages	0.020	0.116	0.022	0.113	−0.002	0.023	0.121	0.018	0.107	0.005
Chemicals	0.026	0.174	0.024	0.151	0.003	0.017	0.121	0.026	0.103	−0.010
Construction	0.030	0.157	0.032	0.127	−0.002	0.020	0.121	0.022	0.107	−0.003
Consumer discretionary	0.018	0.132	0.028	0.121	−0.011	0.019	0.108	0.025	0.125	−0.006
Consumer staples	0.016	0.128	0.026	0.111	−0.010	0.025	0.116	0.015	0.114	0.010
Energy rowhead	0.017	0.142	0.023	0.120	−0.005	0.016	0.120	0.027	0.108	−0.011
Financials	0.018	0.139	0.026	0.125	−0.008	0.022	0.122	0.020	0.105	0.002
Food producers	0.035	0.196	0.015	0.186	0.020	0.014	0.115	0.026	0.114	−0.012
Glass	0.023	0.145	0.026	0.130	−0.002	0.009	0.108	0.037	0.122	−0.028**
Hh. goods & home constr.	0.018	0.147	0.032	0.129	−0.014	0.023	0.112	0.018	0.119	0.006
Ind. Metal & mining	0.019	0.145	0.032	0.136	−0.013	0.025	0.109	0.016	0.122	−0.009
Industrials	0.011	0.138	0.035	0.121	−0.023	0.014	0.114	0.031	0.116	−0.018
Telecom, media, & IT	0.014	0.137	0.026	0.126	−0.012	0.020	0.113	0.022	0.118	−0.003
Travel & leisure	0.011	0.179	0.030	0.149	−0.018	0.015	0.113	0.028	0.116	−0.013
Utilities	0.024	0.137	0.021	0.122	0.003	0.011	0.109	0.034	0.121	−0.022*

Note: Panel A (B) presents the mean and standard deviation of subsequent month market index (industry) returns following positive and negative realization of industry (market) returns during the preceding month. DIF is the difference between mean returns following up and down industry (market) returns in the preceding month. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively.

Table 7
The predictive role of US industries.

	US raw materials→ TRIND		US energy → TRIND		US financials→ TRIND	
	USIND (-1)	t-stat	USIND (-1)	t-stat	USIND(-1)	t-stat
Raw materials	0.175	1.143	0.110	1.007	−0.192	1.523
Beverages	0.204*	1.945	0.080	0.983	−0.132	1.278
Chemicals	0.169	1.115	0.125	1.145	−0.228	1.524
Construction	0.338**	2.040	0.176	1.506	−0.331***	2.872
Consumer discretionary	0.148	1.058	0.048	0.442	−0.223*	1.883
Consumer staples	0.097	0.801	−0.024	0.248	−0.201*	1.724
Energy	0.175	1.276	0.096	0.943	−0.163	1.365
Financials	0.067	0.494	−0.112	0.977	−0.194	1.383
Food producers	−0.073	0.394	−0.198	1.414	0.008	0.058
Glass	0.056	0.437	−0.094	0.908	−0.169	1.210
Hh. goods & home constr.	0.080	0.522	0.003	0.024	−0.250**	2.015
Ind. Metal & mining	0.205	1.209	0.172	1.325	−0.200	1.521
Industrials	0.245*	1.767	0.148	1.377	−0.261**	2.221
Telecom, media, & IT	0.005	0.038	−0.025	0.271	−0.128	1.178
Travel & leisure	0.090	0.645	−0.058	0.528	−0.444***	2.693
Utilities	0.118	1.070	−0.066	0.769	−0.242**	2.082

Note: This table reports the results of predictive regressions, shown in Equation (5), that measure the predictive power of three leading US industries, namely US raw materials, US energy, and US financials, over 16 domestic industries. The columns USIND(-1) report $\beta_{3,i}$ in Equation (5) with the corresponding t -statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors reported in the column next to each estimate. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively.

leads 12 out of 16 Turkish industries. However, Panel B indicates that the predictive role of US industries largely vanishes in the period after the GFC, in which US basic materials leads only three Turkish industries (beverages, construction, and industrial metal and mining), and US energy leads only two Turkish industries (construction and financials). This implies that the ability of the lagged US industry returns to predict industry returns in Türkiye is less pronounced during the US economic expansion after the GFC. This finding is consistent with those of

Monteiro et al. (2023), who documents that informational delays in the response of global market participants are more noticeable during periods of recession in the US, when cross-country correlations are higher. Accordingly, our findings imply that the information from US industries spreads gradually to global equity markets, with a delay during recessions, as investors often struggle to quickly extract the valuable information embedded within industry returns.

In additional unreported results (available from the author upon request), in line with our findings for domestic industries reported in Section 3.1.1, we find that IPO activity does not have a significant impact on the predictive power of US industries on Turkish industries. But we find that foreign ownership has a major impact on the predictive role of US industries. The predictive role of US industries declines during periods of low foreign ownership, in particular, with respect to US basic materials and financials. Although US basic materials loses its predictive role over Turkish chemicals, construction, consumer staples, and household goods and home construction during periods of low foreign ownership, US financials loses its predictive role over Turkish consumer discretionary, energy, and travel and leisure industries. These additional findings establish a close association between the presence of foreign investors in the stock market and the diffusion of information from US industries to Turkish industries.

The results on the impact of the decline in real interest rates in Türkiye are similar. The predictive role of US industries decreases for all three leading US industries during period of high negative real interest rates, in line with our earlier findings for periods of low foreign ownership. We find that US basic materials loses its predictive role on Turkish beverages and utilities and US energy loses its predictive role over Turkish beverages, household goods and home construction, and industrial metals and mining, whereas US financials loses its predictive role over Turkish basic materials, construction, energy, financials, industrials, and telecom, and media and IT. Overall, these findings confirm our earlier inferences that foreign participation in the stock market facilitates the diffusion of information from US industries to Turkish industries.

We next test the out-of-sample predictive performance of US industries over Turkish industries. Again, we follow Zhang et al. (2022) and examine the out-of-sample forecasts by comparing the MSPEs of null and alternative models as follows.

$$R_{i,t} = \beta_{1,i} + \beta_{2,i}R_{i,t-1} + \beta_{3,i}R_{j,t-1}^{U.S.} + \beta_{4,i}INF_{t-1} + \beta_{5,i}MVOL_{t-1} + \varepsilon_{it} \quad (9)$$

where $R_{j,t-1}^{US}$ is the lagged excess return for the leading US industry j in month $t-1$. Equation (9) is the unrestricted (alternative) model, whereas the revised version of Equation (9), which omits $R_{j,t-1}^{US}$, is the restricted (parsimonious) model.

Table 8 gives the MSPE estimates for the restricted and unrestricted forecasting models, showing that US basic materials has out-of-sample predictive power over seven Turkish industries (beverages, chemicals, construction, energy, industrials, telecommunications, media and IT, and utilities), but US energy has out-of-sample predictive power over two Turkish industries (construction and financials). Finally, US financials has out-of-sample predictive power over five Turkish industries (construction, consumer discretionary, household goods and home construction, industrials, and travel and leisure). Overall, the findings indicate that US industries, in particular basic materials and financials, have out-of-sample predictive power over Turkish industries.

Table 9 indicates that the signals from US industry returns could be used to take positions in most Turkish industries. In Panels A and B, the results for US basic materials and US energy are largely insignificant, but with significant differences in the returns in 13 of the 16 Turkish industries after positive and negative fluctuations in US financials. As shown in Panel C, the mean return on Turkish chemicals after upward (downward) movement in US financials is 1 percent (6%). DIF is -5 percent, which is statistically significant. This return spread corresponds to roughly 60 percent on an annual basis, which is significant both economically and statistically. The pattern in 12 industries is similar, and the return spread is 36–48 percent on an annual basis. Overall, our results suggest that the predictive relationship between US industries, in particular financials, and their counterparts on the BIST can be used to design profitable industry-timing strategies for Turkish investors.

4. Conclusion

Predictability in stock market returns is of great interest to active investors and fund managers who time their investment depending on the direction of the market. Although many empirical studies have examined return predictability in financial markets using various techniques, most of them are empirical without basing their analysis on an established theory about the persistence of return predictability. In contrast, the gradual diffusion of information hypothesis of Hong et al.

(2007) presents a theoretical framework to establish a predictive relationship between industry returns and the aggregate stock market index. They argue that public information is frequently manifested in asset prices only in part, because traders concentrating on the broad market index encounter delays in accessing industry-specific information that is already accessible to investors specializing in specific industries. In this study, we test this hypothesis in an emerging market context by exploring the predictive role of industries over the aggregate stock market. However, unlike Hong et al. (2007), we also consider causality from the market to the industries and extend our analysis to an out-of-sample forecasting setting. This is an important consideration not only from a market efficiency perspective but also from an investment point of view, as this predictive relationship between industries and the market could be exploited by investors with active timing strategies.

Using monthly industry portfolio returns for 16 industries and the aggregate stock market index for BIST, we show that travel and leisure is the only industry that has predictive ability over the aggregate market during the sample period. This finding is consistent with prior literature that establishes a direct link between the tourism industry in Türkiye and economic growth (e.g., Ayaydin et al., 2019; Fareed et al., 2018; Ohlan, 2017). This suggests that money managers who specialize in this industry have a competitive advantage over passive index investors, who experience delays in receiving industry-specific information. However, we do not observe a notable structural change in the predictive relationship between industry and aggregate market returns around the establishment of the PDP, which standardized the disclosure of firm-level information across the market. In-sample analyses using different empirical specifications indicate that three industries (travel and leisure, construction, and beverages) mainly play a leading role in the market.

Extending our analysis to an out-of-sample context, we show that several industries (basic materials, consumer staples, and household goods and home construction) have out-of-sample predictive power over the aggregate market. However, this out-of-sample predictive ability cannot be exploited to obtain economic gains by investing in the market index based on the direction of industry returns in the previous month. Finally, we find that US industry returns have greater predictive power over industry returns in Türkiye than the returns of Turkish industries. Consistent with Monteiro et al. (2023), who find that the returns of US

Table 8
Out-of-Sample Forecasting Analysis: Predictability from US industries.

	US raw materials→ TRIND			US energy→ TRIND			US financials→ TRIND		
	Restricted	Unrestricted	ENC-t	Restricted	Unrestricted	ENC-t	Restricted	Unrestricted	ENC-t
	MSE	MSE		MSE	MSE		MSE	MSE	
Raw materials	0.008	0.008	0.508	0.008	0.008	0.493	0.008	0.008	0.062
Beverages	0.006	0.006	2.224***	0.006	0.006	0.821	0.006	0.006	−0.319
Chemicals	0.009	0.009	1.297*	0.009	0.010	0.471	0.009	0.010	0.737
Construction	0.010	0.009	2.142***	0.010	0.010	1.285*	0.010	0.010	1.546**
Consumer discr	0.008	0.008	0.739	0.008	0.008	0.530	0.008	0.008	1.178*
Consumer staples	0.007	0.007	0.764	0.007	0.007	0.621	0.007	0.007	0.644
Energy	0.008	0.008	1.455**	0.008	0.008	0.465	0.008	0.008	0.225
Financials	0.009	0.009	0.903	0.009	0.009	1.199*	0.009	0.010	0.015
Food producers	0.038	0.038	−1.475	0.038	0.038	0.723	0.038	0.038	−1.137
Glass	0.011	0.011	0.072	0.011	0.011	−0.671	0.011	0.011	−0.411
Hh. goods & home constr.	0.010	0.010	0.038	0.010	0.010	0.528	0.010	0.010	1.239*
Ind. Metal & mining	0.011	0.011	0.931	0.011	0.011	0.712	0.011	0.011	0.179
Industrials	0.008	0.008	2.240***	0.008	0.008	0.912	0.008	0.008	1.619**
Telecom, media, & IT	0.005	0.005	1.012*	0.005	0.005	0.761	0.005	0.005	0.519
Travel & leisure	0.015	0.015	−0.078	0.015	0.015	0.514	0.015	0.015	2.002**
Utilities	0.010	0.010	1.425**	0.010	0.010	−0.946	0.010	0.010	0.038

Note: This table presents the mean squared prediction error estimates for the restricted and unrestricted forecasting models. The restricted (parsimonious) model used in the null hypothesis of predictability from leading US industry to Turkish industry is modified version of Equation (9), where $R_{j,t-1}^{US}$ is omitted while the alternative (unrestricted) model is stated in Equation (9). The first half of the sample is used as the initial estimation sample and the second half as the out-of-sample prediction sample as we generated one-step-ahead forecasts via rolling regressions. ENCt denotes the encompassing t -statistic, which adjusts the MSPE to account for the sampling error that leads to an upward bias in the MSPE of the unrestricted model. *, **, and *** significant at the 10, 5, and 1 percent levels, respectively based on the critical values provided by Clark and West (2007).

Table 9

Economic implications of predictability from US industries.

	Panel A: US raw materials → TRIND					Panel B: US energy → TRIND					Panel C: US financials → TRIND				
	Positive		Negative		DIF	Positive		Negative		DIF	Positive		Negative		DIF
	Mean	Stdev	Mean	Stdev		Mean	Stdev	Mean	Stdev		Mean	Stdev	Mean	Stdev	
Raw materials	0.03	0.11	0.02	0.14	0.02	0.03	0.12	0.02	0.13	0.01	0.02	0.13	0.04	0.12	−0.03*
Beverages	0.02	0.10	0.02	0.13	0.01	0.02	0.11	0.02	0.12	0.00	0.01	0.11	0.03	0.12	−0.02
Chemicals	0.04	0.16	0.01	0.17	0.03	0.04	0.17	0.01	0.16	0.02	0.01	0.17	0.06	0.15	−0.05***
Construction	0.05	0.14	0.01	0.15	0.04***	0.04	0.13	0.02	0.16	0.01	0.02	0.15	0.05	0.14	−0.03*
Consumer discretionary	0.03	0.11	0.02	0.15	0.01	0.02	0.12	0.02	0.13	0.00	0.01	0.13	0.04	0.12	−0.03**
Consumer staples	0.03	0.11	0.01	0.14	0.02	0.02	0.11	0.02	0.13	−0.01	0.01	0.13	0.04	0.11	−0.03**
Energy	0.02	0.12	0.02	0.15	0.00	0.02	0.12	0.02	0.15	0.01	0.01	0.14	0.04	0.12	−0.03*
Financials	0.03	0.12	0.02	0.15	0.01	0.02	0.13	0.02	0.14	−0.01	0.01	0.14	0.04	0.12	−0.03**
Food producers	0.03	0.16	0.03	0.22	0.00	0.02	0.17	0.04	0.22	−0.02	0.02	0.20	0.04	0.18	−0.01
Glass	0.03	0.13	0.02	0.15	0.01	0.02	0.14	0.03	0.14	0.00	0.01	0.14	0.04	0.13	−0.03**
Hh. goods & home constr.	0.03	0.13	0.02	0.15	0.01	0.02	0.13	0.03	0.15	0.00	0.01	0.15	0.05	0.13	−0.04**
Ind. Metal & mining	0.02	0.13	0.02	0.15	0.01	0.02	0.13	0.02	0.15	−0.01	0.01	0.14	0.04	0.13	−0.03*
Industrials	0.03	0.11	0.01	0.15	0.02	0.02	0.12	0.02	0.14	−0.01	0.01	0.14	0.04	0.12	−0.03**
Telecom, media, & IT	0.02	0.11	0.01	0.15	0.01	0.02	0.11	0.02	0.15	−0.01	0.01	0.13	0.03	0.13	−0.02
Travel & leisure	0.02	0.14	0.02	0.20	−0.01	0.01	0.17	0.02	0.16	−0.01	0.00	0.18	0.04	0.15	−0.04**
Utilities	0.04	0.13	0.01	0.13	0.03*	0.02	0.12	0.02	0.14	0.00	0.01	0.12	0.05	0.14	−0.04***

Note: Panels A, B, and C present the mean and standard deviation of subsequent domestic industry returns following positive and negative realization of US raw materials, energy, and financials returns during the preceding month. DIF is the difference between mean domestic industry returns following upward and downward US industry returns in the preceding month. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

industries significantly Granger cause the returns of most other countries' industries, we find that Turkish industry returns have a delayed response to new information from US industries, in particular, financials. This creates an opening for industry investment strategies by local investors conditional on US industry return dynamics. Our findings show that foreign participation in the stock market facilitates the diffusion of information from US industries to Turkish industries and the economic benefits from these spillover effects can be as high as 60 percent on annual basis, particularly if industry investment is conditioned on signals from US financials.

In sum, our findings show that industry returns have predictive information regarding the direction of the aggregate market, both in- and out-of-sample, and this predictive power is often magnified during a

crisis. Furthermore, industry information from the US stock market has significant spillover effects on local Turkish industry returns, and these spillover effects can be profitably used by local investors to time industry portfolio allocations. Our findings have significant investment implications for investors as well as being of great interest to market regulators, because information from leading industries, particularly US financials, can be integrated into forecasting models to monitor stock market dynamics in Türkiye, enabling them to take appropriate action, particularly during a crisis.

In future research, it would be interesting to extend our analysis to a large number of emerging markets by also considering the role of market liquidity in the predictive relationships between industries and the aggregate market.

APPENDIX

Appendix Table A1

The impact of local crises on the predictive relationship between the market and industries

	Panel A: IND → MKT					
	IND(-1)	t-stat	D	t-stat	D*IND(-1)	t-stat
Raw materials	0.050	0.542	−0.072*	1.778	0.844*	1.689
Beverages	0.154	1.525	−0.067	1.372	−0.140	0.416
Chemicals	0.028	0.730	−0.091*	1.878	0.312	1.407
Construction	0.022	0.299	−0.064	1.297	−0.080	0.148
Consumer discretionary	−0.052	0.429	−0.065	1.448	−0.471	0.465
Consumer staples	0.160	1.045	−0.066	1.492	−0.715	0.928
Energy	−0.086	1.040	−0.085	1.529	0.639	1.000
Financials	−0.010	0.077	−0.070*	1.764	−0.300	0.432
Food producers	0.020	0.596	−0.065	1.218	−0.031	0.084
Glass	−0.103	1.256	−0.056	1.210	0.803***	2.629
Hh. goods & home constr.	0.039	0.367	−0.066	1.432	0.071	0.089
Ind. Metal & mining	0.031	0.445	−0.068	1.527	0.383	0.754
Industrials	0.034	0.349	−0.071	1.408	0.220	0.217
Telecom, media, & IT	0.110	0.750	−0.062	1.108	−0.042	0.090
Travel & leisure	−0.112**	2.186	−0.070	1.447	−0.153	0.376
Utilities	−0.017	0.174	−0.064	1.338	0.083	0.185
	Panel B: MKT → IND					
	MKT(-1)	t-stat	D	t-stat	D*MKT(-1)	t-stat
Raw materials	0.092	0.772	−0.060	1.622	−1.288***	3.623

(continued on next page)

Appendix Table A1 (continued)

	Panel B: MKT → IND					
	MKT(-1)	t-stat	D	t-stat	D*MKT(-1)	t-stat
Beverages	0.086	0.940	0.010	0.257	0.037	0.170
Chemicals	0.049	0.366	-0.145**	2.064	-1.429***	4.071
Construction	0.012	0.115	-0.081	1.470	-0.540	1.014
Consumer discretionary	0.007	0.046	-0.090*	1.869	0.121	0.107
Consumer staples	-0.135	0.942	-0.087	1.610	0.318	0.356
Energy	0.069	0.576	-0.028	0.500	-0.738	1.511
Financials	0.153	0.787	-0.075*	1.749	-0.281	0.292
Food producers	0.254**	2.128	-0.015	0.374	-0.691***	3.152
Glass	0.285**	2.103	0.009	0.119	-1.154**	2.079
Hh. goods & home constr.	0.032	0.203	-0.095*	1.690	-0.292	0.272
Ind. Metal & mining	-0.049	0.405	-0.048	0.979	-1.021*	1.753
Industrials	-0.037	0.340	-0.068	1.136	-0.012	0.009
Telecom, media, & IT	-0.082	0.513	-0.092	1.208	-0.688	0.770
Travel & leisure	-0.029	0.196	-0.111**	2.225	-0.272	0.601
Utilities	0.085	0.661	-0.058	1.485	-0.134	0.244

Note: This table presents the results of estimating Equations (3) and (4), where D is a dummy variable that equals one during local crises as per Comert and Yeldan (2018), and zero otherwise. In Panel A, the column IND(-1) reports the estimates for $\alpha_{2,i}$ in Equation (3), while in Panel B, the column MKT(-1) reports $\beta_{3,i}$ in Equation (4). The interaction terms D*IND(-1) and D*MKT(-1) represent $\alpha_{7,i}$ and $\beta_{7,i}$ in Equations (3) and (4), respectively. The *t*-statistics based on Newey–West heteroskedasticity and serial correlation correction standard errors are reported in the column next to each estimate. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A2

The impact of the 2008 global financial crisis on the lead-lag relationships

	Panel A: IND → MKT					
	IND(-1)	t-stat	D	t-stat	D*IND(-1)	t-stat
Raw materials	0.054	0.592	-0.008	0.272	0.181	0.968
Beverages	0.193*	1.688	-0.007	0.247	-1.025***	2.661
Chemicals	0.053	1.051	-0.013	0.468	0.043	0.437
Construction	0.017	0.215	-0.008	0.291	-0.045	0.229
Consumer discretionary	-0.171	1.133	-0.006	0.228	0.717***	2.740
Consumer staples	0.068	0.380	-0.008	0.270	-0.073	0.128
Energy	-0.078	0.892	-0.006	0.226	0.394	1.061
Financials	0.013	0.086	-0.009	0.316	0.153	0.191
Food producers	-0.001	0.031	-0.008	0.301	0.418***	4.067
Glass	-0.029	0.297	-0.012	0.395	-0.376	0.856
Hh. goods & home constr.	-0.021	0.182	-0.008	0.319	0.388**	2.359
Ind. Metal & mining	0.021	0.279	-0.008	0.271	0.184	0.988
Industrials	0.026	0.235	-0.010	0.335	-0.155	0.578
Telecom, media, & IT	0.131	0.930	-0.012	0.436	-0.530***	2.448
Travel & leisure	-0.121**	2.049	-0.008	0.272	0.108	0.586
Utilities	-0.026	0.251	-0.007	0.277	0.226	1.323

	Panel B: MKT → IND					
	MKT(-1)	t-stat	D	t-stat	D*MKT(-1)	t-stat
Raw materials	-0.012	0.093	-0.014	0.420	-0.063	0.168
Beverages	0.068	0.748	0.005	0.264	0.417***	3.171
Chemicals	-0.134	0.826	0.037	1.290	0.421	1.052
Construction	-0.082	0.730	-0.019	0.630	0.081	0.216
Consumer discretionary	0.068	0.378	-0.006	0.212	-0.665**	2.602
Consumer staples	-0.116	0.700	-0.009	0.316	0.108	0.322
Energy	-0.032	0.259	-0.009	0.357	0.040	0.066
Financials	0.046	0.218	-0.007	0.186	-0.256	0.214
Food producers	0.187	1.539	-0.030	0.977	-0.340	1.473
Glass	0.131	0.794	-0.037	0.991	0.636	1.191
Hh. goods & home constr.	0.039	0.235	-0.009	0.246	-0.359	1.092
Ind. Metal & mining	-0.161	1.257	-0.015	0.443	0.074	0.179
Industrials	-0.102	0.796	-0.014	0.585	0.384	1.330
Telecom, media, & IT	-0.188	1.031	-0.009	0.327	0.190	0.761
Travel & leisure	-0.131	0.835	0.013	0.390	0.397	1.006
Utilities	0.003	0.021	0.013	0.331	0.209	0.637

Note: This table presents the results of estimating Equations (3) and (4), where D is a dummy variable that equals one during the 2008 global financial crisis (Aug. 2007–Sept. 2009), and zero otherwise. In Panel A, the column IND(-1) reports the estimates for $\alpha_{2,i}$ in Equation (3), while in Panel B, the column MKT(-1) reports $\beta_{3,i}$ in Equation (4). The interaction terms D*IND(-1) and D*MKT(-1) represents $\alpha_{7,i}$ and $\beta_{7,i}$ in Equations (3) and (4), respectively. The *t*-statistics based on Newey–West heteroskedasticity and serial correlation correction standard errors are reported in the column next to each estimate. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A3
The impact of the COVID-19 pandemic

	Panel A: IND → MARKET					
	IND(-1)	t-stat	D	t-stat	D*IND(-1)	t-stat
Raw materials	0.094	1.079	0.013	0.409	1.336***	2.998
Beverages	0.158	1.396	0.015	0.664	-1.266***	3.567
Chemicals	0.049	1.170	0.038	1.588	-1.395	1.436
Construction	0.014	0.183	0.022	0.863	0.232	0.823
Consumer discr	-0.064	0.419	0.001	0.050	-0.671***	2.774
Consumer staples	0.052	0.295	0.008	0.287	0.271	1.059
Energy	-0.057	0.647	0.005	0.171	-0.248	0.468
Financials	0.009	0.063	0.019	0.714	0.810	1.390
Food producers	0.015	0.431	0.012	0.385	0.074	0.753
Glass	-0.037	0.381	0.027	1.061	0.921**	2.427
Hh. goods & home constr.	0.036	0.328	-0.011	0.334	-0.835	1.472
Ind. Metal & mining	0.042	0.576	0.013	0.407	0.939***	3.716
Industrials	-0.004	0.038	0.048**	2.117	1.809***	3.084
Telecom, media, & IT	0.087	0.641	0.075***	4.376	-2.143***	10.389
Travel & leisure	-0.124**	2.162	0.028	1.391	0.418**	1.983
Utilities	0.004	0.041	0.033	1.558	-1.446	1.626
	Panel B: MARKET → IND					
	MKT(-1)	t-stat	D	t-stat	D*MKT(-1)	t-stat
Raw materials	0.017	0.245	0.003	0.118	-0.716***	3.730
Beverages	-0.056	1.038	0.004	0.211	1.262**	2.376
Chemicals	0.020	0.213	0.033*	1.850	0.460	1.040
Construction	-0.033	0.351	0.016	0.997	0.215	1.364
Consumer discr	-0.079	1.185	-0.043	1.104	2.426***	7.216
Consumer staples	-0.029	0.433	0.049*	1.666	0.117	0.571
Energy	-0.100*	1.639	-0.054	1.171	0.636	1.137
Financials	-0.031	0.464	0.022	0.753	-1.469	1.482
Food producers	0.150	1.424	0.126*	1.785	0.563	1.270
Glass	0.080	0.917	0.011	0.383	-0.442	1.058
Hh. goods & home constr.	-0.051	0.667	-0.075**	1.815	2.254**	2.288
Ind. Metal & mining	-0.049	0.636	-0.004	0.154	-0.664***	3.883
Industrials	-0.114**	2.034	0.029	1.170	-0.680***	2.751
Telecom, media, & IT	-0.111	1.565	0.097***	9.016	1.144***	12.955
Travel & leisure	-0.183**	1.985	-0.015	0.391	0.113	0.217
Utilities	0.000	0.003	0.036*	1.750	1.583**	2.468

Note: This table presents the results of estimating Equations (3) and (4), where D is a dummy variable that equals one during the COVID-19 pandemic (Dec. 2019–June 2020), and zero otherwise. In Panel A, the column IND(-1) reports the estimates for $\alpha_{2,i}$ in Equation (3), while in Panel B, the column MKT(-1) reports $\beta_{3,i}$ in Equation (4). The interaction terms D*IND(-1) and D*MKT(-1) represent $\alpha_{7,i}$ and $\beta_{7,i}$ in Equations (3) and (4), respectively. The *t*-statistics based on Newey–West heteroskedasticity and serial correlation correction standard errors are reported in the column next to each estimate. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table A4
The global financial crisis and the predictive role of US industries

	Panel A: Pre–Global Financial Crisis						Panel B: Post– Global Financial Crisis					
	US raw materials		US energy		US financials		US raw materials		US energy		US financials	
	USIND(-1)	t-stat	USIND(-1)	t-stat	USIND(-1)	t-stat	USIND(-1)	t-stat	USIND(-1)	t-stat	USIND(-1)	t-stat
Raw materials	-0.027	0.103	0.048	0.235	-0.450**	2.223	0.056	0.371	0.102	1.077	0.127	1.313
Beverages	0.251	0.971	0.183	0.803	-0.272	1.397	0.175*	1.678	0.094	1.220	0.005	0.050
Chemicals	0.076	0.218	0.288	1.040	-0.368	1.447	0.106	0.701	0.093	0.816	-0.011	0.086
Construction	0.223	0.725	0.201	0.817	-0.597***	2.987	0.246*	1.811	0.109*	1.691	-0.137	1.312
Consumer discretionary	0.106	0.369	0.194	0.770	-0.509**	2.475	-0.023	0.194	-0.029	0.334	0.077	0.899
Consumer staples	0.078	0.272	0.185	0.670	-0.438**	2.057	-0.014	0.139	-0.103	1.138	0.037	0.399
Energy	0.080	0.279	0.168	0.713	-0.405**	2.103	0.021	0.184	-0.010	0.109	0.051	0.513
Financials	0.186	0.604	0.176	0.603	-0.568**	2.555	-0.122	0.894	-0.253***	2.740	0.172	1.578
Food producers	0.078	0.218	0.180	0.772	0.096	0.397	-0.294	1.019	-0.364	1.492	-0.004	0.027
Glass	-0.102	0.378	-0.145	0.617	-0.488**	2.500	0.185	1.249	0.041	0.405	0.124	0.849
Hh. goods & home constr.	0.133	0.403	0.234	0.817	-0.505**	2.174	-0.150	1.277	-0.105	1.287	0.021	0.233
Ind. Metal & mining	0.092	0.328	0.283	1.075	-0.445*	1.846	0.211*	1.838	0.112	1.533	-0.093	1.078
Industrials	0.062	0.208	0.225	0.955	-0.470**	1.986	0.048	0.256	0.103	0.932	0.122	1.168
Telecom, media, & IT	0.017	0.051	0.199	0.717	-0.287	1.255	0.076	0.864	-0.026	0.307	0.035	0.476
Travel & leisure	-0.017	0.055	0.012	0.047	-0.835***	2.925	0.007	0.046	-0.146	1.111	-0.040	0.337
Utilities	0.177	0.689	0.081	0.364	-0.485***	2.832	0.058	0.532	-0.025	0.266	0.005	0.042

Note: This table reports the results of predictive regressions, shown in Equation (5), that measure the predictive power of three leading US industries, namely US raw materials, US energy, and US financials, over 16 domestic industries. Panels A and B report the findings for the periods before the global financial crisis (January 1995–June 2007) and after the global financial crisis (October 2009–March 2022), respectively. The column USIND(-1) reports $\beta_{3,i}$ in Equation (5) with the corresponding *t*-statistics based on Newey–West heteroskedasticity and serial correlation corrected standard errors reported in the column next to each estimate. *, **, and *** represent significance at the 10, 5, and 1 percent levels, respectively.

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