Economic News Impact Analysis Using Causal-Chain Search from Textual Data

Kiyoshi Izumi[1], Shintaro Suda[2], and Hiroki Sakaji[1]
[1] School of Engineering, the University of Tokyo, 7-3-1 Hongo, Bunkyo, 113-8656 Tokyo, JAPAN
[2] Mitsubishi UFJ Trust Investment Technology Institute Co., Ltd.
izumi@sys.t.u-tokyo.ac.jp

Abstract

In this research, we extract causal information from textual data and construct a causality database in the economic field. Furthermore, we develop a method to produce causal chains starting from phrases representing specific events and offer possible ripple effects and factors of particular events or situations. Using our approach to Japanese textual data, we developed a method to select stocks related to specific news. We created lists of related companies and measured impacts on those stock prices for the two important news about a wheat price in 2018. As a result, the market impacts appeared in the companies related to the ripple effects when the news is about the obvious fact. In contrast, it appeared in the companies related to the remote causes when the news is about the opinion and decision.

Introduction

The impact of news on financial markets is not fixed. For example, news “an increase in the US consumer price index” can lead to a weakening of the dollar in currency markets from the perspective of purchasing power. The same news, however, can lead to a stronger dollar from the perspective of inflation and rising interest rates. The market impact depends strongly on the economic and political situation at the time the news is released. It also depends on market participants' perceptions of the current economic situation.

It is beneficial to construct a database of economic causality and analyze the relationship between causality for both financial professionals and non-specialists. Such technology can support the prediction of market impacts caused by the news because market participants' perceptions mainly consist of economic causality information. It is, however, difficult to analyze the causality between economic phenomena only by the statistical analysis of numerical data. That is because human activities produce a causal relationship between economic events. Human activities are determined by mental processes such as cognition, thinking, and emotion. Thus, economic causality is influenced by social and cultural situations. It is almost impossible to extract objective and universal causality by statistical analysis of numerical data like natural scientific phenomena.

In this research, we propose a method to create an economic causal-chain network from economic text data in Japanese. The economic causal-chain refers to a cause and effect network structure formed by extracting a description indicating a causal relationship from the texts of financial statement summaries. In other words, it is a network that includes causal relationships that investors have recognized from financial statement summaries. Using the causal chain constructed by this method, we developed a method to select stocks related to specific news.

Related works

Much work has been done on the extraction of causal information from texts. Inui et al. proposed a method for extracting causal relations (*cause*, *effect*, *pre-cond,* and *means*) from complex sentences containing the Japanese resultative connective “ため (*tame*: because)” (Inui, T.; Inui, K.; Matsumoto, Y. 2004), as this is a reliable indicator of causal information. Khoo et al. proposed a method to extract cause-effect information from newspaper articles by applying manually created patterns (Khoo, C.; Kornfilt, J.; Oddy, R.; Myaeng, S.-H. 1998). They also obtained causal knowledge from medical databases by applying their graphical patterns (Khoo, C.; Chan, S.; Niu, Y. 2000). Chang et al. proposed a method to extract causal relationships between noun phrases using cue expressions and

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word pair probabilities (Chang, D.-S., and Choi, K.-S. 2006). They defined as the probability that the pair forms a causal noun phrase. Girju proposed a method for automatic detection and extraction of causal relations based on cue phrases, where pairs of noun phrases express causal relationships (Girju, R. 2003). Girju used WordNet (Fellbaum, C. 1998) to create semantic constraints for selecting candidate pairs, so her method cannot extract unknown phrases that are not in WordNet. Bethard et al. proposed a method for classifying verb pairs that have causal relationships using an SVM for classification (Bthard, S., and Martin, J. H. 2008). Sadek et al. proposed a method for extracting Arabic causal relations using linguistic patterns represented using regular expressions (Sadek, J., and Meziane, F. 2016). In contrast, our approach extract not only cause-effect expressions but also construct causal chains.

Ishii et al. proposed a method for constructing causal chains using WordNet and SVO tuples (Ishii, H.; Ma, O.; Yoshikawa, M. 2012). They employ the process of (Sakaji, H.; Sekine, S.; Masuyama, S. 200) for extracting cause-effect expressions. Alashri et al. proposed a method to extract causal relations and construct causal chains from large text corpora related to climate change (Alashri, S.; Tsai, J.-Y.; Koppela, A. R.; Davulcu, H. 2018). However, their approach cannot build causal chains when expressions consist of noun phrases. Because their method targets expressions that include Subjects, Verbs, and Objects (SVO). On the other hand, our method can construct causal chains from expressions that consist of noun phrases only.

Recently, several studies on extracting causal information from text data in the financial field have also been published (Dasgupta, T.; Saha, R.; Dey, L.; Naskar, A. 2018)(Hassanzadeh, O.; Bhattacharjya, D.; Feblowitz, M.; Srinivas, K.; Perrone, M.; Sohrabi, S.; Katz, M. 2019). Nakagawa et al. proposed a method to exploit the lead-lag effect in stock markets using the economic causal-chain (Nakagawa, K.; Sashida, S.; Sakaji, H.; Izumi, K. 2019). There are, however, still a few studies on the application of causal information in financial markets.

Causal Chain Search from Textual Data

In this study, we analyze Japanese economic text data that seems to contain causality recognized by humans and construct a database of causality related to the economic field. For example, the Japanese sentence "円高のため、日本経済は悪化した。(*endaka no tame nihonkeizai ha akkashita*: Because of the yen's appreciation, the Japanese economy deteriorated.)" includes cause expression "円高 (*endaka*: the yen's appreciation)" and effect expression "日本経済は悪化した。(*nihonkeizai ha akkashita*: the Japanese economy deteriorated.)." Our method extracts these cause-effect expressions using clue expressions. In this case, the clue expression is "ため (*tame*: because)."

Furthermore, we develop a method to search for causal chains derived from phrases representing specific events. Using this method, we implement a system that can display causal chains for user's input words and select appropriate sequences or delete inappropriate sequences. Our method consists of the following steps.

1. Step 1 extracts sentences that include cause-effect expressions (causal sentences) from Japanese financial statement summaries using a support vector machine.
2. Step 2 obtains cause-effect expressions from the extracted sentences using syntactic patterns.
3. Step 3 constructs economic causal-chains by connecting each cause-effect expression.

Step 1 and Step 2 are implemented by a method of (Sakaji, H.; Murono, R.; Sakai, H.; Bennett, J.; Izumi, K. 2017).

Step 1: Extraction of Causal Sentences

We developed a technique for extracting causal sentences from economic texts. It may be challenging to distinguish causal sentences. For instance, the Japanese clue expression "ため (tame: because)" is essential for extracting cause-effect expressions, but it can also be used to mean an objective. For example, the Japanese sentence "あなたのために、花を買った。(anata no tame ni hana wo katta: I bought some flowers for you)" includes the clue expression "ため (tame: because)," but it does not have a causal meaning in this context. We will, therefore, develop a method for extracting sentences that include cause and effect expressions that can cope with such situations.

Since this method uses a support vector machine (SVM) for extraction, we explain how to acquire features from financial statement summaries. Our approach uses the features shown in Table 1 to extract causal sentences. We employ both syntactic and semantic features.

Table 1. Features for the extraction of causal sentences.

Kinds of features	Features
Syntactic features	Pairs of particles
Semantic features	Extended language ontology
Other features	Part of speech of morphemes just before clue expressions
	Morpheme unigrams
	Morpheme bigrams

We aim to use expressions that are frequently used in cause and effect expressions in sentences as syntactic features. For example, the Japanese sentence "半導体の需要回復を受けて半導体メーカーが設備投資を増やしている。(*handoutai no jyuyoukaifuku woukete hanndoutaime-ka-ga setsubitoushi wo fuyashiteiru*: As semiconductor demand recovers, semiconductor manufacturers are increasing their capital investment.)" has the following pattern of particles and clue expressions: "... の ... を受けて ... を ... (... *no* ... *woukete* ... *wo* ...)." This pattern indicates that it is highly likely to be a cause-effect expression. Our method, therefore, acquires particles that relate to clue expressions using a Japanese syntactic parser.

Besides, our method acquires words indicating causality using an extended language ontology (Kobayashi, A.; Masuyama, S.; Sekine, S. 2010). Fig. 1 shows our process of obtaining a semantic feature. Here, a **core phrase** is the last part of a phrase that includes a clue expression, and a **base point phrase** is a phrase that is modified by the core phrase. First, our method acquires words that modify the core phrase or the base point phrase. Then, a tuple of concept words that are obtained by tracing extended language ontology using the words is acquired as a syntactic feature. Here, each tuple consists of two concept words, one based on the core phrase and the other based on the base point phrase.

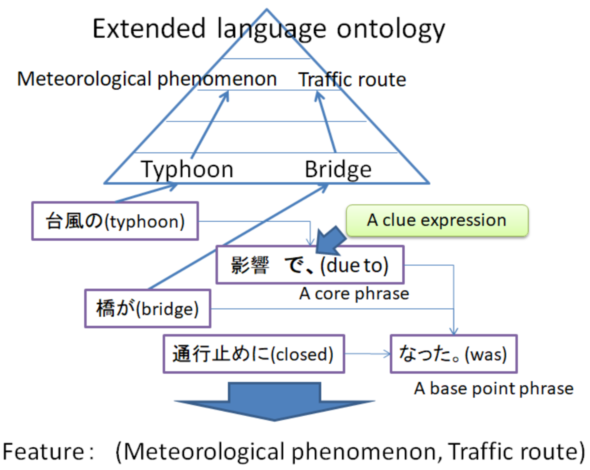

Fig. 1. An example of a semantic feature.

Step 2: Extracting Cause-Effect Expressions

We employ a method by [3] to extract cause-effect expressions using four syntactic patterns. We analyzed sentence structures and used a pattern matching method with syntactic patterns is shown in Fig. 2. In Fig. 2, "Cause" indicates a cause expression, "Effect" denotes an effect expression, and "Clue" indicates a clue expression. Sakaji et al. [3] used a Japanese dependency analyzer [4] to analyze Japanese syntax, but the recall of that method is too low for our needs. However, the technique is not enough about the recall. Therefore, to improve the recall of the method, we add a new syntactic pattern (Pattern E).

Pattern A is the most basic pattern for expressing causality in Japanese. The others derive from Pattern A to emphasize either cause or effect, as represented by the arrows in Fig. 2.

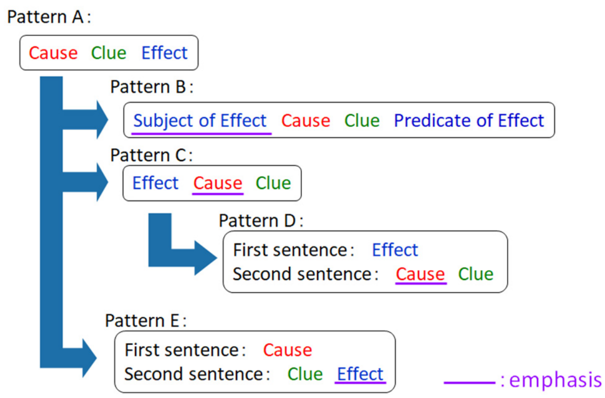

Fig. 2. A syntactic patterns list.

To illustrate the operation of our method, we now work through examples using two of the five syntactic patterns (Patterns A and C). Fig. 3 shows our method of extracting cause and effect expressions using Pattern A. It first identifies core and base point phrases using the clue expression "を背景に (*wohaikeini*: with)." Then, the cause expression "半導体メーカーの設備投資の拡大 (*handoutaimeka-nosetsubitoushinokakudai*: expansion of capital investment by semiconductor manufacturers)" is extracted by tracking back through the syntactic tree from the core phrase. Finally, the effect expression ``半導体製造装置向け制御システムの販売が伸びた。(*handoutaiseizousouchimukeseigyosisutemunohannbaiganobita*: sales of control systems for semiconductor manufacturing equipment increased)" is extracted by tracking back through the syntactic tree from the base point phrase.

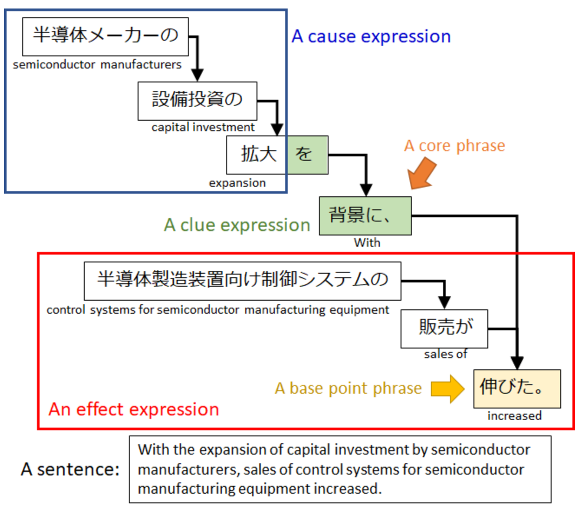

Fig. 3. An example of pattern A.

Fig. 4 shows our method extracting cause and effect expressions using Pattern C. It first identifies core and base point phrases using the clue expression "ためだ。(*tameda*: because)." Then, the cause expression "国際線が好調なのは (*kokusaisengakoutyounanoha*}: International airlines are doing well)" is extracted by tracking back through the syntactic tree from the core phrase. Finally, the effect expression "欧米路線を中心にビジネス客が増えた (*oubeirosenwotyushinnibijinesukyakugafueta*}: the number of business customers increased mainly in Euro-American airlines)" is extracted by tracking back through the syntactic tree from the base point phrase.

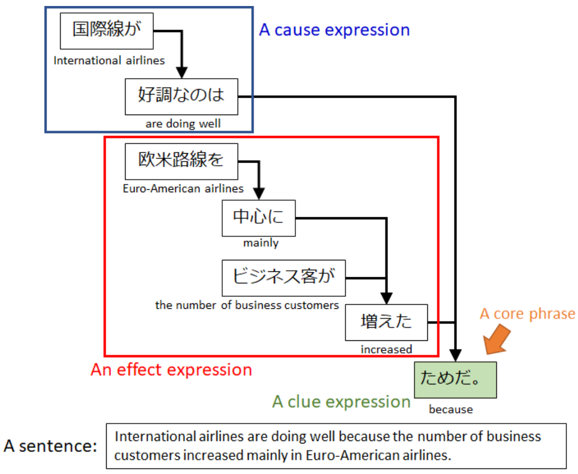

Fig. 4. An example of pattern C.

Step 3: Constructing Causal Chains

To construct causal chains, our method (Sakaji, H.; Sekine, S.; Masuyama, S. 2008) connects an effect expression of a cause-effect expression and a cause expression of another cause-effect expression. We show an algorithm of constructing causal chains in Fig. 5.

Input: A list of cause–effect expressions CI
CI_i = (Cause Expression c_i, Effect Expression e_i, Company cp_i, Date d_i)
Output: A list of causal chain LCC
$LCC \leftarrow \emptyset$
for each $(c_i, e_i, cp_i, d_i) \in CI$ **do**
  for each $(c_j, e_j, cp_j, d_j) \in CI$ **do**
    $similarity \leftarrow getSimilarity(e_i, c_j)$
    if $similarity \geq threshold$ **then**
      $LCC \leftarrow LCC + (c_i, e_i, cp_i, d_i, c_j, e_j, cp_j, d_j)$
    end if
  end for
end for
return LCC

Fig. 5. Construction of causal chains.

In Fig. 5, "Company" indicates the company that issues the financial statement summary from which the cause-effect expression has been extracted. Additionally, "Date" is the date the financial statement summary was published. In Fig. 5 getSimilarity$(e_i; c_i)$ is a function that calculates the similarity between the effect expression e_i and the cause expression c_j. Our method estimates the similarities based on vectors of word embedding. First, our method obtains word embedding average of the words included in the expressions. Here, we define the average obtained from the effect expression e_i as $\widetilde{W}_{e_i}$ and the average obtained from the cause expression c_j as $\widetilde{W}_{c_i}$. $\widetilde{W}_{e_i}, \widetilde{W}_{c_i} \in R^m$ and m is the dimension size of word embedding. Then, our method calculates a cosine similarity between $\widetilde{W}_{e_i}$ and $\widetilde{W}_{c_i}$ and employs the similarity as the similarity between the effect expression e_i and the cause expression c_j. Finally, our approach acquires pairs of cause-effect expressions as a causal chain when the similarities are larger than a threshold.

That method can be applied to both the forward search and backward search. In the forward search, a user can find the ripple effects of an input phrase (Fig.6a). The input text is considered the first causal expression, and our algorithm tries to finds cause-effect expressions as a chain in order of cause and effect. In the backward search, a user can find remote causes of an input phrase (Fig.6b). The input text is considered the first effect expression, and our algorithm tries to finds cause-effect expressions as a chain in order of effect and cause.

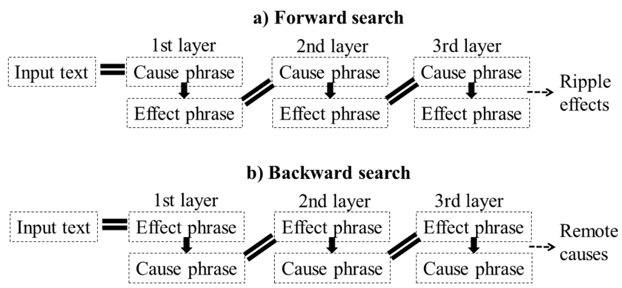

Fig. 6. Forward and backward causal chains.

Empirical Study: News Impact Analysis

Dataset and Methodology

In this section, we examine the news impact analysis using the economic causal-chain of the previous section.

Textual data: As a source of causal information, we used about 20,000 financial statement summaries from October 2012 to May 2018. They were published by about 2,300 companies listed on the Tokyo Stock Exchange. A financial statements summary is a common form report that is disclosed when a listed company announces its financial performance (balance sheet, cash flows, operating results, and business risks). It contains various causal information. For example, "full-year same-store sales declined due to issues with product mixes and volume planning," and "lower estimated future cash flows or a higher discount rate would cause further impairment losses." We extracted 1,078,542 pairs of cause-effect expressions from those Japanese documents using the method as mentioned earlier.

Selection of companies: In this study, we focused on news about wheat prices in commodity markets. First, we created a causal chain starting from the phrase "wheat price," using the method mentioned in fig. 5. The maximum number of causal chain layers is 3. The threshold of similarity is 0.65. Fig. A shows a part of a forward causal-chain starting from "wheat price." Each cause-effect expression relates to a particular company that published a financial statement summary, including the expression. In each layer of a causal chain, we listed up related companies that appeared for the first time in that layer. Those companies are considered to be affected by news about wheat prices in commodity markets. The related company lists are created for both forward and backward causal-chains.

Event study: During the out-of-sample period after May 2018, we focused on the following two days. On these days, important news about wheat prices was published in the Nihon Keizai Shimbun, Japan's most significant economic newspaper.

- Case 1: (July 24 2018) "International wheat price of is high for the first time in a month with the prospect of reduced production in France."
- Case 2: (September 6 2018) "Wheat international price drops by 4%. Russia says, "No export restrictions."

To measure an impact on the financial market, we used an absolute value of an excess return.

$$|r_{i,t} - R_t|,$$

where $r_{i,t}$ is a price return of a company i,

$$r_{i,t} = \frac{p_{i,t} - p_{i,t0}}{p_{i,t0}}.$$

$p_{i,t}$ is a closing price of company i at day t. t_0 is a day when the important news was released (July 24, 2018 or September 6, 2018). R_t is a benchmark,

$$R_t = \frac{P_t - P_{t0}}{P_{t0}}.$$

P_t is a closing price of TOPIX, a stock index of the Tokyo Stock Exchange, at day t. t ranges from -20 (20 days before t_0) to $+20$ (20 days after t_0).

In this study, we did not distinguish between positive and negative relationships in a cause-effect expression and connection between expressions. Thus, the current method cannot deal with the direction (positive and negative) of an impact. It can measure only an amplitude of a market impact. Then, we did not use a raw value of an excess return, but an absolute value.

Results and Discussion

We created lists of related companies and measured impacts on those stock prices for the two important news about a wheat price (Case 1 and 2).

Selection of companies: As mentioned, first we constructed 3-layer causal-chains starting from "wheat price" for each direction (forward and backward) like Fig. A. Tables 2 and 3 show the companies that appeared at the first time in each layer of the forward and backward causal-chain, respectively.

Table 2. Related companies in the forward causal-chain from "wheat price."

Layer	Ticker code (company name)
1st	2002 (Nisshin Seifun Group Inc.)
	2003 (Nitto Fuji Flour Milling Co., Ltd.)
	2212 (Yamazaki Baking Co., Ltd.)
	3306 (The Nihon Seima Co., Ltd.)
2nd	4042 (Tosoh Corporation)
	4185 (JSR Corporation)
	5632 (Mitsubishi Steel Mfg. Co., Ltd.)
3rd	2802 (Ajinomoto Co., Inc.)
	4569 (Kyorin Holdings, Inc.)
	4726 (SB Technology Corp.)
	5104 (Nitto Kako Co., Ltd.)
	5406 (Kobe Steel, Ltd.)
	5542 (Shinhokoku Steel Corporation)
	5697 (Sanyu Co., Ltd.)
	5801 (Furukawa Electric Co., Ltd.)
	6334 (Meiji Machine Co., Ltd.)
	7965 (Zojirushi Corporation)

In Table 2, the depth of the company's layer reflects the deepness of the relationship between a wheat price and that company. For example, the companies in the first layer deal with products made of wheat, such as flour (2002, 2003, and 3306) and bread (2212). As the layers deepen, the relationship with wheat becomes indirect. Chemical makers (4042 and 4185) appeared in the second layer. Steel companies (5632, 5406, and 5542) appeared in the second and third layers. Chemical and steel companies are indirectly linked to wheat prices in terms of raw material prices, including crude oil. Besides, the condiment maker (2802) and the pharmaceutical company (4569) appeared in the third layer. Notably, the machine manufacturers (6334) in the third layer specializes in grain milling machines, so the trend of grain prices, including wheat, affects its demand trend and performance. The cooking device manufacturer (7965) in the third layer produces oven toasters, home bakery, and hot plates. Sales of those devices are influenced by a decline in consumer demand with increased grain prices.

Table 3. Related companies in the backward causal-chain from "wheat price."

Layer	Ticker code (company name)
1st	2002 (Nisshin Seifun Group Inc.) 2003 (Nitto Fuji Flour Milling Co., Ltd.) 2215 (First Baking Co., Ltd.)
2nd	2001 (Nippon Flour Mills Co., Ltd.) 6250 (Yamabiko Corporation)
3rd	8031 (Mitsui & Co., Ltd.)

Also, in the backward causal-chain, directly related companies (2002, 2003, and 2215) appeared in the first layer (Table 3). As you move back in the causal chain, companies that deal with a broader range of products appear. For example, an agricultural machinery manufacturer (6250) appeared in the second layer, and a trading firm (8031) appeared in the third layer. The backward causal-chain is a good indicator of the spread of the remote causes.

Event study (Case 1): Fig. 7 shows the average of absolute excess returns in each layer of the forward causal-chain in Case 1 (July 24 2018).

$$\frac{1}{n}\sum_{i=1}^{n}\left|r_{i,t} - R_t\right|,$$

where n is a number of companies in the layer.

The stock prices of related companies moved clearly after the news release. The impact of stock prices at a deeper layer was larger and lasted longer. Those results show that the market impact of the news has amplified to a broader range of stocks over time.

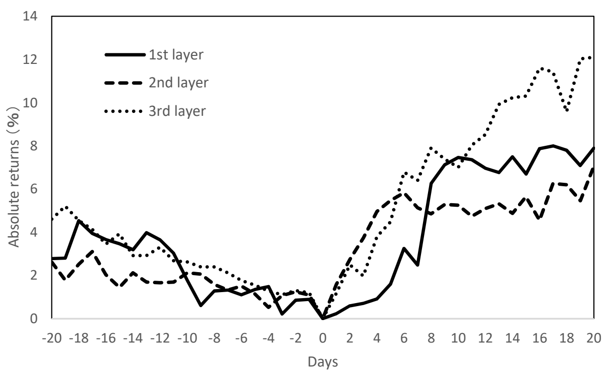

Fig. 7. Average of absolute excess returns in each layer of the forward causal-chain in Case 1 (July 24 2018).

Fig. 8 shows the average of absolute excess returns in each layer of the backward causal-chain in Case 1. In this case, the stock prices of the related companies did not change their price trends.

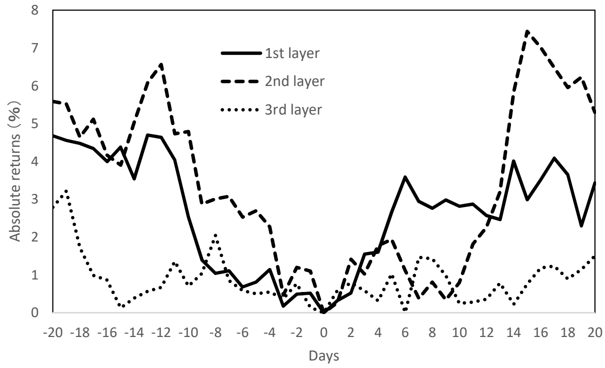

Fig. 8. Average of absolute excess returns in each layer of the backward causal-chain in Case 1 (July 24 2018).

Event study (Case 2): Fig. 9 shows the average of absolute excess returns in each layer of the forward causal-chain in Case 2 (September 6 2018). In this case, the stock prices of the related companies in the forward causal-chain did not change their price trends. In contrast, the stock prices of the related companies in the backward causal-chain moved after the news release (Fig. 10).

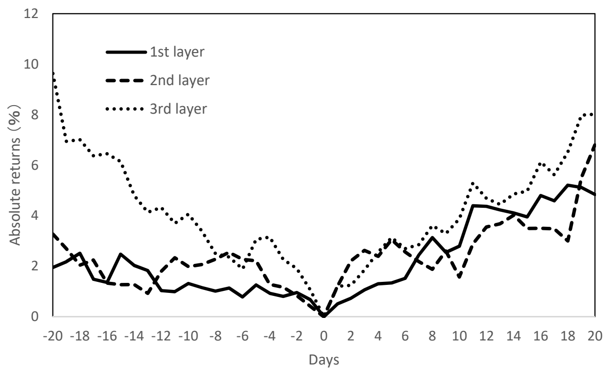

Fig. 9. Average of absolute excess returns in each layer of the forward causal-chain in Case 2 (September 6 2018).

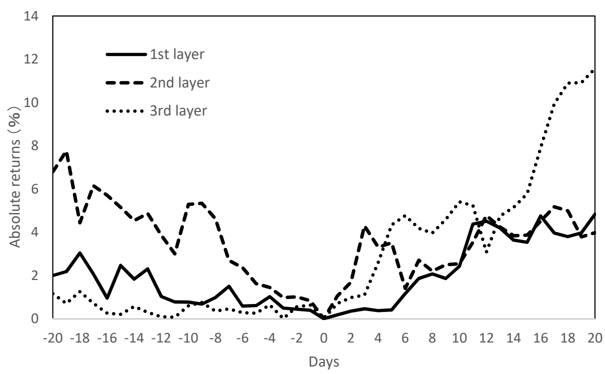

Fig. 10. Average of absolute excess returns in each layer of the backward causal-chain in Case 2 (September 6 2018).

Discussions about differences in Case 1 and 2: Case 1 and 2 showed the opposite results: There were impacts on the companies related to the ripple effects in Case 1. There were impacts on companies related to the remote causes in Case 2. Those differences would have been caused by differences in the content of the news. In Case 1, the news was related to the apparent fact, "the reduced production in France." Market participants would focus only on the results caused by this fact. That was because the reasons for this fact are not essential for financial markets. In Case 2, the news was related to Russian decision, "no export restrictions." Market participants would have tried to find the economic and political background of the decision. They then focused on the companies related to the remote causes of the decision.

Conclusions

In this research, we propose a method to select companies affected by certain news using economic causal-chains. The economic causal chain refers to a cause and effect network structure created by extracting a description indicating a causal relationship from the texts of the financial statement summaries. We created lists of related companies and measured impacts on those stock prices for the two important news about a wheat price in 2018. As a result, the market impacts appeared in the companies related to the ripple effects when the news is about the obvious fact. In contrast, it appeared in the companies related to the remote causes when the news is about the opinion and decision.

There are some extensions of the proposed method as future work. First, we are going to apply our method to English textual data, such as financial news articles and financial reports. Besides, we are going to develop a method to add positive and negative relationships to the causal chain. That makes it possible to analyze the direction of the market impact. The economic causal-chain search algorithm can be used for various financial information services. We want to launch some of the following services in collaboration with financial institutions or financial information vendors.

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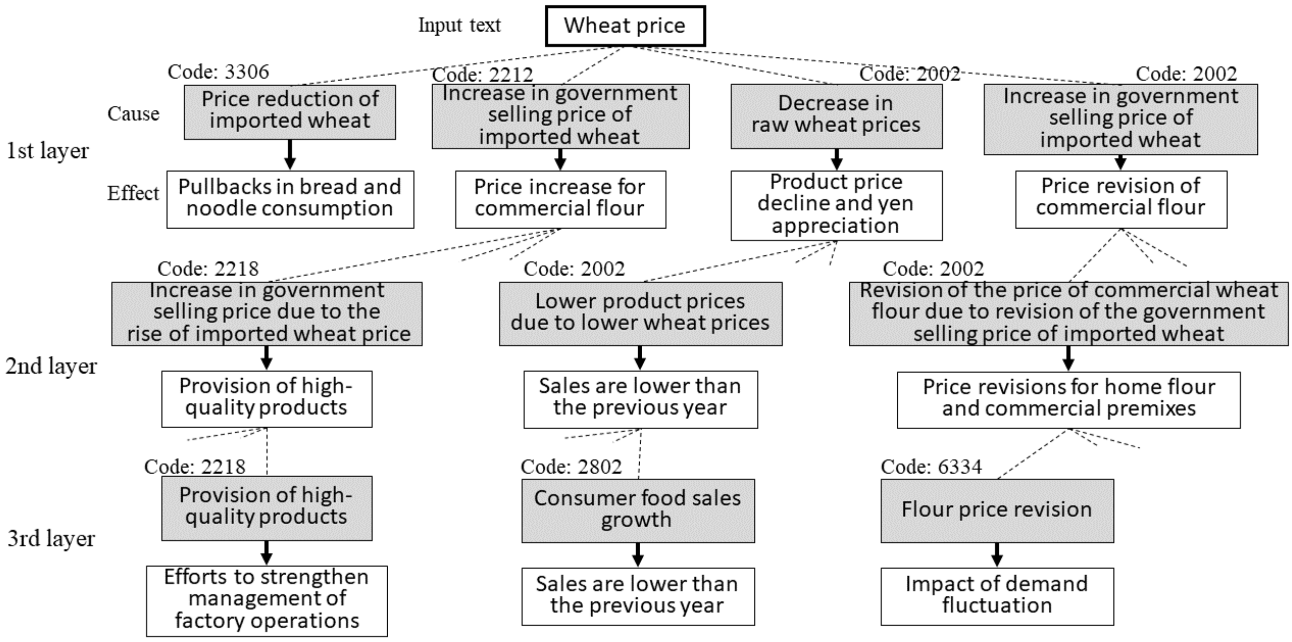

Fig. A. A part of a forward causal-chain starting from "wheat price". A gray (white) box means a cause (effect, respectively) expression. A solid arrow (dotted line) stands for causality (similarly, respectively). *Code* means a ticker code of a company that published the cause-effect expression. Original texts are written in Japanese.