Information Decay and Firm Valuation – Evidence from Taiwan's Biotech Industry

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We investigate the capabilities of predicting firm value over different time horizons based on the data from Taiwan's biotech industry. The variables of ROA, ROE, operating profit margin, net income ratio, Tobin's Q and stock price are used to measure firm value. These variables are either being predicted separately or together as a whole, and prediction accuracy is tested across different predictor variable time lags. A 2-quarter lag appears to result in a better prediction for ROE, stock price and net income ratio, and a 1-quarter lag for ROA, regardless of whether a single variable is being predicted or several combined. Using very recent information does not necessarily lead to effective firm valuation as information decay may not be an immediate effect. This implies cost savings from keeping various financial and non-financial factors up-to-date which may be tedious and time consuming.

INTRODUCTION

Biotechnology has been considered as a contemporary technology with great profit generating potential since 1970s. However, investing in the biotech sector involves considerable risk, where historically more failures than successes have been observed. To better understand a company's fundamentals, investors seek to identify relevant useful data to predict stock value directly and/or indirectly. Due to the unique innovation-driven nature of biotech industry, the valuation of biotech companies involves a broad spectrum of considerations, including both financial factors commonly used for estimating/forecasting corporate value and certain types of non-financial factors such as patents and R&D pipeline activities.

It may require great effort to keep current with recent financial and non-financial information for firm valuation. Lack of the most recent data could compromise predictive accuracy; however, it takes time for the market to react to certain information because the information may not be immediately understood. That implies that information can be still useful for learning and forecasting the dynamics of the market even though it is not very recent. Thus, the effect of information decay should be examined for factors used to predict firm or stock value. Given a set of time series data, we can study the relationship of the output variable(s) (i.e. the variable(s) used to measure firm value) to the information content of predictor factors that lag behind by different time periods.

Taiwan's biotech sector presents an emerging Asian market and serves as the case study in this research. Note that most biotech companies in Asian countries are relatively less mature than biotech firms in the US or western Europe, and may have a different approach to their development strategy and business model (Lee & Chen, 2010). For example, biotech industry's development in Taiwan has been considerably influenced by strategic involvement of the government. The 1995 Action Plan for Strengthening the Biotechnology Industry was an early government initiative, which certainly opened the avenue for the development. According to the Taiwan Pharmaceuticals and Healthcare Report Q1 2010 by BMI (Business Monitor International), "In 2006, biotech investment exceeded US$700 million, with the country boasting over 1,100 biotechnology and biomedical firms and a joint business turnover of US$6 billion, which grew at an average annual rate of 13% over the 2001-2006 period." Private investment in biotechnology amounted to NT$26.3 ($1NT (Taiwanese dollar or TWD) = $0.03 USD based on the 2009 average yearly exchange rate) billion in 2009 (an increase of 5% from 2008), where annual private investment has been above NT$25 billion throughout the period of 2007-2009. As a result, a total of 42 biotech companies were listed on Taiwan's stock exchange or traded on the OTC market at the end of 2009, with a total sales revenue of NT$47.0 billion in 2009 (an increase of 3.14% compared to NT$45.6 billion in 2008). 25 biotech companies were listed on Taiwan's emerging stock market by the end of 2009, with a total sales revenue of NT$12.42 billion. After the Executive Yuan approved the Diamond Action Plan for Biotech Takeoff in 2009, investment in Taiwan's biotech industry and the output was expected to double after five years.

In 2010, the National Development Fund, Executive Yuan approved 33 domestic and foreign biotechnology investment projects, and these projects call for approved investment of NT$11.2 billion. Business income tax (reduced to 17%) in Taiwan is comparable to nearby countries. In addition, Taiwan signed the Economic Cooperation Framework Agreement (ECFA) with China, including an "early harvest" list of tariff reductions. Clearly, Taiwan is aiming at the international biotech market, and the above facts show promise for Taiwan's investment environment as a gateway especially into the Asian biotech market.

We believe our analysis of Taiwan's biotech firms will provide investors with a better understanding of how the past information can be used as an effective reference for firm valuation for developing biotech companies not only in Taiwan but also in other countries. This research will provide the answer as to the time horizon over which the future firm value can be efficiently estimated using current data. Since Taiwan's biotech industry is still in the development stage, our investigation should be able to present a comparison result with studies alike for countries which have a more developed structure of biotech industry, such as US and the western European countries.

The rest of the paper is presented as follows. In Section 2, we highlight related studies in the field from existing literature. We describe our data sample and methodology in Section 3. Section 4 summarizes the analysis results and finally, conclusions are drawn in Section 5.

PREVIOUS STUDY RESULTS

Prior studies indicate that the valuation of biotech companies is generally more complicated than that of firms in other industries. One reason is that biotech industry is largely driven by innovation which is different from many traditional industries. Zheng *et al*. (2010) study the influence of the innovative capability and inter-firm network on firm valuation particularly for startup biotech companies. The above implies that, in addition to financial and fundamental factors (e.g. Magni & Vélez-Pareja, 2009; Chandra & Ro, 2008) which people often use to assess the value and potentiality of a company, the indication of certain non-financial factors, particularly R&D activity, should not be overlooked (e.g. Stoneman & Toivanen, 1997; Toivanen *et al*., 2002), patent counts and/or patent citations (Shane & Klock, 1997; Hirschey *et al*., 2001; Trajtenberg, 1990; Chin *et al*., 2006), advertising activity (Hall, 1993), trademarks (Bosworth & Mahdian, 1999) and brand (Kallapur & Sabrina, 2004). Another reason is that in the biotech industry R&D takes longer to result in a market ready product; for example it may be 10 to 15 years before the development of a blockbuster drug in the pharmaceutical industry. Kellogg and Charnes (2000) use the real option method to evaluate biotech companies, but the process involved by using this method is complicated and time consuming, and can only be performed for one company at a time.

Investors tend to seek very recent data for better assessing or predicting the performance of the firm, and use a less complicated analysis method if possible. However, the acquisition of various financial and non-financial factors in a timely matter may require considerable effort and cost, where a tradeoff is expected between our capability in firm valuation and cost savings from keeping relevant and useful information up-to-date. Lee and Chen (2010) and Wang *et al*. (2012) present several variables to measure firm value and apply the stepwise regression method, incorporated with the BPNN (Back-Propagation Neural Networks) method, to analyze the relationship of these variables to various financial and non-financial factors. Although their studies show that the BPNN method improves the result from the traditional regression methods in term of estimating firm value, their analysis uses the data of firm value variables within the same time frame as estimator variables, which we consider needs to be further investigated since in the real world, we intend to use today's information to predict tomorrow's outcome. Thus their approach does not reflect what is being done in practice.

It can take some time for the information to be digested by investors and then reflected in firm value. In other words, older data may be useful, and thus it is possible to save the effort in updating ourselves with up-to-date data for firm valuation without the predicting ability being compromised. More importantly, investors would be interested in learning the time needed for the influence of current events to take effect; that is, how far into the future we can make our predictions for firm value using the current data (Israelov & Katz, 2011). Hence, it is important to study the information decay effect (e.g. Grinold & Kahn, 2011; Olariu & Niekerson, 2008; Kannan *et al*., 2007; Hirtle & Lopez, 1999) for various financial and non-financial factors on the firm value variables in order to better understand the predicting capability of these factors and how they can be effectively used in time.

SAMPLE COLLECTION AND DATA VARIABLES

Our sample data spans from 1997 through 2010, a period of significant growth in Taiwan's biotech industry. Our sample includes all Taiwanese biotech firms defined by ITIS (Industry & Technology Information Services), which are publicly listed by the TSEC (Taiwan Stock Exchange Corporation). Excluding firms that have missing financial statements, the final sample consists of 33 biochemistry firms. Table 1 shows these 33 companies.

We first attempt to obtain a comprehensive data set of financial and non-financial factors that are considered as likely influential variables when estimating corporate value, based on our survey on business reports in Taiwan and interviews with professionals in the field. Financial variables are mostly constructed from the company's financial statement. Non-financial variables generally pertain to intangible assets such as human, relational, intellectual and structural capital (Starovic & Marr, 2008). We consider ROA, ROE, operating profit margin, net income ratio, Tobin's Q and stock price can be indicative of corporate value. For example, there have been studies that use Tobin's Q to represent firm value when investigating the relationship of certain financial and non-financial factors to firm value (Feng & Rong, 2007; Megna & Klock, 1993).

TABLE 1
SAMPLE FIRMS

Company Name	Establishment Date	Capital Investment (NT$)
Actherm Inc.	8/10/1998	500,000,000
Apex Biotechnology Corp.	12/2/1997	1,001,668,000
Apex Medical Corp.	3/17/1990	1,100,000,000
Center Laboratories, Inc.	11/4/1959	1,500,000,000
Chi Xheng Chemical Corp.	10/6/1962	650,000,000
Chia Jei Technology Business Co., Ltd.	5/6/1995	1,000,000,000
China Chemical & Pharmaceutical Co., Ltd	3/12/1952	3,000,000,000
Dr. Chip Biotech. Inc.	10/22/1998	700,000,000
Everlight Chemical Industrial Corp.	9/7/1972	8,000,000,000
Farcent Enterprise Co.	5/24/1983	639,000,000
Gen Mont Biotechnology Inc.	12/6/2000	1,000,000,000
Grape King Biotech	4/1/1971	1,500,000,000
Health & Life Co. Ltd.	12/16/1996	500,000,000
Johnson Health Tech. Co., Ltd.	10/7/1975	2,500,000,000
Level Biotechnology Inc.	12/7/1989	400,000,000
Maywufa Biopharma Group	10/11/976	1,600,000,000
Microlife Corp.	5/3/2000	6,000,000,000
Na Kang Hsiung Enterprise Co. Ltd.	8/20/1973	700,000,000
Namchow Group	6/30/1950	4,000,000,000
Orient Europharma Co., Ltd	6/16/1982	1,000,000,000
Pacific Hospital Supply Co., Ltd.	8/6/1977	1,000,000,000
Pihsiang Machinery Mfg. Co., Ltd.	12/22/1983	4,000,000,000
Rossmax International Ltd.	11/2/1988	1,000,000,000
Sagittarius Life Science Corp.	3/16/1998	600,000,000
Sinphar Pharm. Co., Ltd.	7/2/1977	2,500,000,000
Standard Chem. & Pharm. Co., Ltd.	6/30/1967	2,000,000,000
Synmosa Biopharma	8/25/1970	1,500,000,000
SYN-TECH Chem. & Pharm. Co.	11/9/1982	368,000,000
Taiyen Co. Inc..	7/1/1995	8,000,000,000
TTY Biopharm.	7/22/1960	3,500,000,000
Wei Chuan Corp.	9/22/1953	6,000,000,000
Yung Zip Chemical Co., Ltd.	6/8/1978	700,000,000
Yungshin Pharm Ind. Co. Ltd.	1/3/2011	3,100,000,000

A total of 34 financial and non-financial factors used as predictor variables in this study (see Table 2) are collected given the availability of the data sources. The values of all variables are either directly obtained from, or can be calculated based on the data provided by the information source we used. These factors can be classified into 10 different categories: indexes in the profit and loss statement, indexes in the balance sheet, cost indexes, stock indexes, solvency indexes, human capital, relational capital, organizational capital, technological capital, and intellectual capital.

TABLE 2
PREDICTOR VARIABLES

Indexes in the Profit and Loss Statement	**Indexes in the Balance Sheet**	**Cost Indexes**	**Stock Indexes**	**Solvency Indexes**
Net sales	Total assets	Personnel expense ratio	Earnings per share	Operating profit to paid-in capital ratio
Net income	Shareholder's equity	R&D expense ratio	Outstanding common stock price	Net income to paid-in capital ratio
R&D cost			Price to earnings ratio	
Company size				
Human Capital	**Relational Capital**	**Organizational Capital**	**Technological Capital**	**Intellectual Capital**
Employee productivity	Revenue growth rate	Total asset turnover	R&D intensity	Patent number
Value added per employee	Days sales of inventory	Current asset turnover	R&D productivity	Patent citations
Wealth created per employee	Management advisory fee to net income ratio	Fixed asset turnover	R&D expense to management expense ratio	Innovation and originality
Operating income per employee		Management expense ratio	R&D expenditure to total assets ratio	Goodwill, trademarks and royalties
		Management expense per employee		
		Inventory turnover		

ANALYSIS METHOD AND RESULTS

To study the information decay effect, we have the predictor variables lag by different time periods behind, and analyze their predicting capability to the output variables. We test the time lags by different numbers of quarters up to 1 year. Then, the BPNN method is employed considering its non-restrictive, non-linear and non-parametric traits, and effectiveness in improving the estimation accuracy for firm value (see Lee & Chen, 2010; Wang *et.al*., 2012).

Due to possible non-linear relationships between our data variables and factors, rather than use commonly used linear regression methods, we proceed with the BPNN analysis under two settings, multiple (inputs) vs. one (output) and multiple (inputs) vs. multiple (outputs). In the setting of multiple vs. one, given the number of lagging quarters, the predicting capability using the 34 predictor variables together is tested for each output variable separately (where we need to run 6 separate tests as we have 6 output variables). The other setting is to test the capability of these predictor variables to predict all output variables simultaneously. Note that the BPNN method requires several parameters to be given at the begin of the analysis such as hidden node numbers at different layers of the network, learning rate, inertia factor and learning cycle number. We use the software of PCNeuron 5.0 to implement this technique.

The values of the above parameters are initiated by the software. We then test different values for each parameter to revise its current value while the others remain at their current values. This revision is sequentially applied to the parameters in order to find the value for each which results in a smaller root-mean-square prediction error (by comparing the learning outcome from the learning sample with the test sample). We perform the above operation under two settings: multiple inputs vs. one single output, and multiple inputs vs. multiple outputs. For example, under the first setting the final parameter values we used for each output variable are shown in Table 3.

TABLE 3
BPNN PARAMETER VALUES USED FOR EACH OUTPUT VARIABLE (MULTIPLE VS. ONE)

	Hidden node numbers (layer 1,layer 2)	Learning rate	Inertia factor	Learning cycle number
Tobin's *Q*	(60,10)	1	0.4	50000
ROA	(60,40)	10	0.4	10000
ROE	(10,20)	1	0.4	10000
Stock price	(20,60)	1	0.4	10000
Operating profit margin	(20,0)	1	0.9	20000
Net income ratio	(60,60)	1	0.4	20000

Table 4, Figures 1 and 2 show the BPNN prediction results using MAD (Mean Absolute Deviation) to measure the prediction error. Lag-*x* indicates that the time period of the predictor variables falls behind the output variables by *x* quarters, where x = 1, 2, 3 or 4. According to these table and figures, we have the observations as follows.

TABLE 4
MADS FOR THE BPNN PREDICTION RESULTS

Multiple vs. One				
	Lag-1	Lag-2	Lag-3	Lag-4
Tobin's Q	0.273	0.273	0.494	0.470
ROA	0.232	0.267	0.401	0.259
ROE	0.218	0.111	0.362	0.236
Stock price	0.250	0.220	0.372	0.398
Operating profit margin	0.244	0.021	0.169	0.186
Net income ratio	0.125	0.039	0.174	0.198
Multiple vs. Multiple				
	Lag-1	Lag-2	Lag-3	Lag-4
Tobin'sQ	0.270	0.313	0.753	0.648
ROA	0.245	0.267	0.670	0.298
ROE	0.209	0.109	0.371	0.633
Stock price	0.274	0.253	0.310	0.511
Operating profit margin	0.115	0.130	0.141	0.380
Net income ratio	0.158	0.155	0.163	0.342

FIGURE 1
MADS OF THE BPNN PREDICTION RESULT (MULTIPLE VS. ONE)

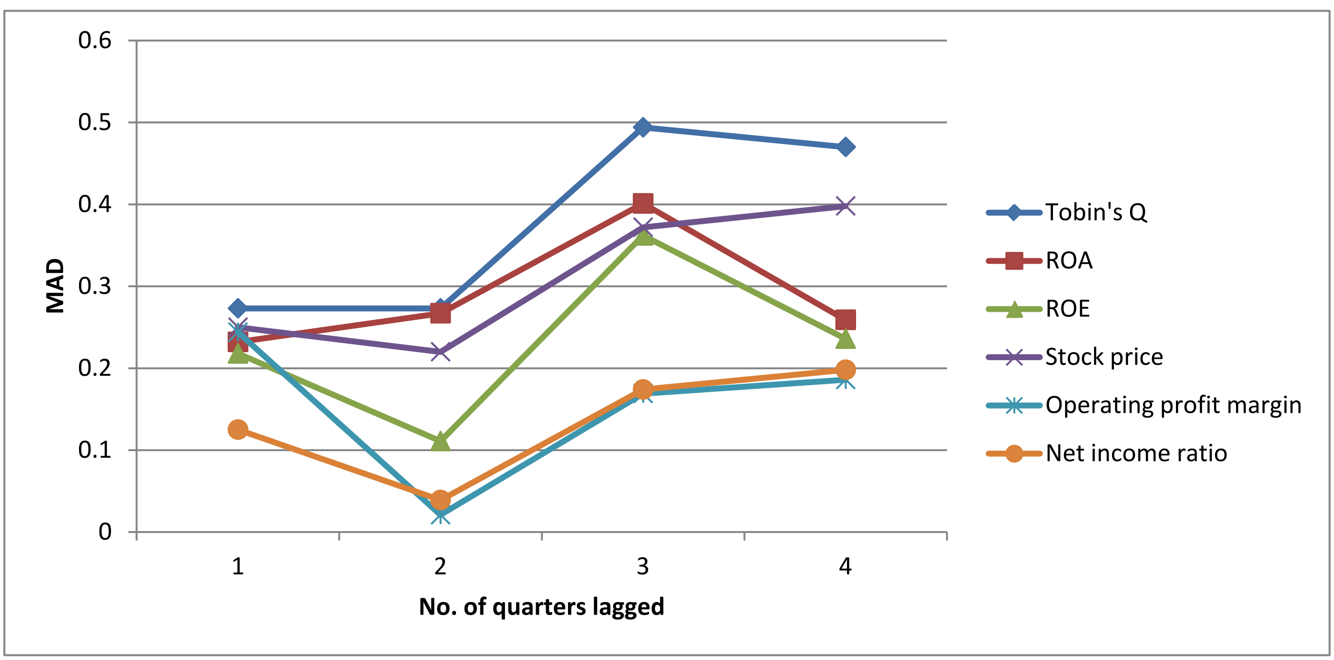
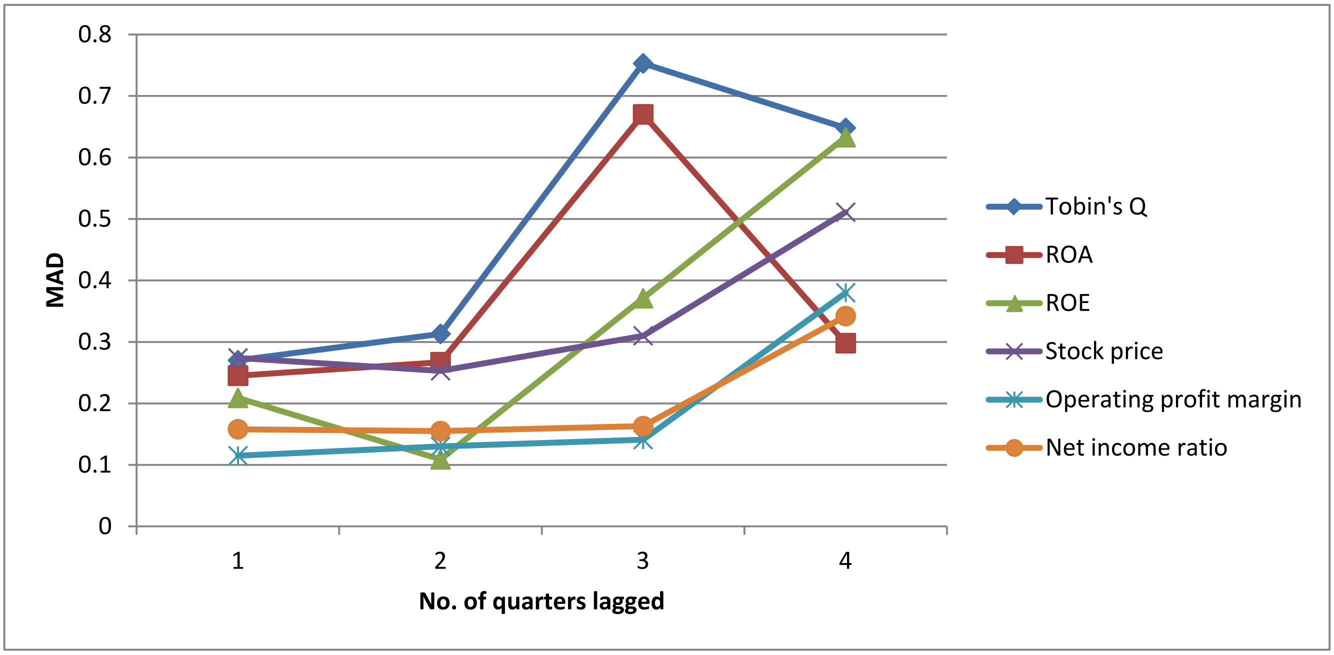


FIGURE 2
MADS OF THE BPNN PREDICTION RESULT (MULTIPLE VS. MULTIPLE)



When only one single variable (ROA, ROE, operating profit margin, net income ratio, Tobin's Q or stock price) is being predicted for firm valuation (i.e. the multiple vs. one setting), the 1-quarter-earlier predictor data is recommended for predicting ROA, either 1 or 2 quarters earlier for Tobin's Q, and 2 quarters for the other output variables. Compared with the least MADs to be likely achieved using predictor data lagging by the above recommended time periods for each output variable, there is a noticeable MAD increase in the prediction outcome if using even older data. This presents the evidence of the information decay effect in general. However, for ROA the 4-quarter-earlier data may be the second candidate if the 1-quarter-earlier data cannot be available in time.

Similarly, when several variables combined are being predicted for firm valuation (the multiple vs. multiple setting), the 1-quarter-earlier predictor data is recommended for predicting ROA, Tobin's Q and operating profit margin, and 2 quarters for the other output variables. Again, the evidence of the information decay effect is found by comparing the least MADs when the 1- or 2-quarter-earlier predictor data is used, with the noticeably higher MADs when the older predictor data is used. However, for ROA the older data may be still useful for prediction (except for 3 quarters earlier) if the 1-quarter-earlier data cannot be available in time.

We conclude that the 34 predictor variables we use appear to have the best prediction outcome for firm value within the time window of 2 quarters. The outcomes for ROA and Tobin's Q (ROA in particular) have the best accuracy over the window of just 1 quarter, and ROE, stock price and net income ratio can be effectively predicted using the 2-quarter-earlier predictor data with the least error, regardless of whether they are being used individually (multiple vs. one) or combined with other variables (multiple vs. multiple) for firm valuation. Once it goes beyond the 2-quarter time frame, the prediction accuracy more or less decreases (i.e. with an increasing MAD) where the information decay effect takes place. The above effect is especially noticeable for stock price, operating profit margin and net income ratio which can be seen by comparing the trend of their increasing MADs with that of the other firm value variables (see Figures 1 and 2).

CONCLUDING REMARKS

Considerable return that can be generated from investments in the biotech industry within a relatively short time period is attractive to adventurous investors. For a developing biotech environment like Taiwan, the future it has presented shows promise and thus has drawn attention from many investors. Firm valuation is clearly one important exercise for investors to foresee whether and/or where the opportunity exists.

Due to the innovation-driven nature of the biotech industry and the discussions from previous studies, besides commonly used fundamental financial factors, our study incorporates various non-financial factors such as intellectual property, patent, and R&D activities etc. into analysis. Considering the cost of extensively retrieving the up-to-date content of various financial and non-financial factors, our goal is to help investors to find a comprehensive, however, efficient method of using data that exists already for effective firm valuation. In the meantime, we hope to identify the preferred time horizons for effective prediction of different firm value variables. To achieve the above goals, the information decay effect of the predictor variables on firm value is investigated in our study.

We use the BPNN method because previous studies have suggested it be an effective method when estimating output variables given the values of estimator variables. Our result indicates that the time window of 2 quarters is generally the time frame over which an effective prediction of firm value may be achieved, especially for Tobin's Q, ROE, stock price and net income ratio. The prediction time window of ROA appears to be shorter that the above by 1 quarter and that of Tobin's Q can be 1 or 2 quarters, which implies more recent data should be used for the prediction of ROA and Tobin's Q. This might be because these two variables are an asset based return indicator, where an update value may be more reflective on the company's current condition than other equity or sales level based variables (asset is usually hard to be manipulated than equity or sales level). However, the predictor data somewhat earlier than 1 quarter may be still useful for predicting ROA since the change of the prediction outcome by using earlier data does not seem to be as significant as the change when earlier data is used for predicting the other output variables.

Note that when the lag is more than the 2 quarters where the information decay effect appears to be greater, the prediction accuracy by using the 4-quarter lag data however improves over that by using a 3-quarter lag for the output variables of ROA and Tobin's Q. We speculate that a seasonal effect may be one reason where the same quarter data from last year weighs in when we make predictions. We leave this for our future research.

In summary, we would like to highlight our observation of the influence of the predictor information on the prediction outcome, where the older data sometimes shows to be more useful than the recent. This seems to contradict the common practice where we intend to use concurrent or recent data to estimate/predict the future. One simple explanation is that the information (financial and/or non-financial) may take the investor's time to digest to be reflected in the dynamics of the market such as firm value. In other words, the life of the information of some types of financial and non-financial factors can be longer than that we have considered. Our analysis builds on the developmental data of Taiwan's biotech firms, and we hope the findings provide certain insights into the role of the past information as an effective reference for firm valuation for developing biotech companies not only in Taiwan but also in other countries. In addition, in the field of portfolio management a portfolio generally is constructed based on various financial and non-financial factors; our result suggests the manager might want to hold portfolios for a longer period until next rebalancing which implies a lower cost for information updating/retrieval.

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