Efficiency and Book-to-Market Ratios of U.S. Pharmaceutical Firms

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Using data envelopment analysis (DEA), we calculate sales efficiency for U.S. pharmaceutical firms and find it to be positively associated with those firms' book-to-market ratios (a measure widely used in the finance literature to estimate the risk and growth potential of firms' common stock). Thus, we conclude that sales-efficient firms in this industry are, on average, undervalued and suggest that the U.S. pharmaceutical industry is characterized by firms making off-balance sheet investments, which we argue leads to efficiency during our sample years (2009-2015). We also conduct longitudinal analyses and conclude that firms in our sample with smaller asset levels are more efficient. Finally, we conduct a slack analysis, which concludes that most of the overvalued companies exhibit inefficiencies in their utilization of research and development costs and selling, general, and administrative costs. Fewer of those firms exhibit inefficient utilization of their costs of goods sold.

Keywords: book-to-market ratio, data envelopment analysis (DEA), off-balance sheet investment, sales efficiency, slack analysis, U.S. Pharmaceutical Industry

INTRODUCTION

The United States is the largest pharmaceuticals market in the world (Fitch Solutions, 2021), and its competitive landscape has shifted significantly in recent years. The sources of the shift mainly come from public scrutiny on healthcare costs and the technological advancement of big data. The 2010 Affordable Healthcare Act (ACA) dramatically increased the number of U.S. residents covered by health insurance, reduced the prices of branded drugs (Spatz, 2010), mandated generic drugs in certain areas, imposed fees on pharmaceutical companies (Daemmrich, 2011), and extended patent-protection period of biologics to 12 years (The Pew Charitable Trusts, 2017). These regulations make branded drugs accessible to larger population, however, they also restrict pharmaceutical companies' ability to profit from pricing. In addition to increased political pressure, the digital age also intensifies competition in the pharmaceutical industry. Many start-ups can now monitor patients precisely by using big data, sensors, and artificial intelligence (Kafel, 2017). In response to heightened competition, large pharmaceutical companies seek to merge with smaller companies that have developed new drugs as well as those that have created apps to collect massive data related to diseases. They also invest in artificial intelligence and machine learning, trying to minimize research and development (R&D) expenses (First Research, 2021). Besides fending off competition by R&D and sales channels, pharmaceutical companies strive to manage the supply chain to enhance gross profit and earnings before interest and taxes (EBIT). These changes make the financial prospects of U.S. pharmaceutical companies uncertain and prompted us to learn more about how the difference between the value presented on the financial statements (book value) and the value perceived by investors (market value) is affected by efficiency of R&D expense, marketing expense, and cost of goods sold (COGS).

Success in the pharmaceutical industry requires intensive research and development investment (Xu and Cavusgi, 2019; Tyagi *et al*., 2018; Khanna *et al*., 2016; Mahajan *et al.*, 2014), costly marketing and advertising expenditure (Agarwal *et al.*, 2020; Rahman *et al.*, 2020; Goncharuk and Getman, 2014), contentious political management and pricing strategies (Martin *et al*., 2018; Altug and Sahin, 2018; Comanor *et al.*, 2018), as well as complicated supply chain management (Kumar et al., 2018; Huq *et al.*, 2016). All these challenges are potential risks to investors because the cost of these investments may not be capitalized on the balance sheet (in the book value). Therefore, the value of the company perceived by the investors (market value) often diverges from the book value, resulting in firms' book-to-market ratios (BM) to different than one. Since BM is associated with a risk premium (Alam *et al*., 2014), we are interested in exploring how pharmaceutical companies' BM reacts to multiple risks at the same time. Because most pharmaceutical companies report marketing and advertising expenses as a component of Selling, General, and Administrative Expense (SG&A) (Schweitzer and Lu, 2018), we use SG&A as a surrogate for marketing expense.

R&D, SG&A, and COGS each has its own effect on the difference between market value and book value, and they affect each other (Arnold and Troyer, 2016), however, investors need a general view of how these critical costs affect company value. When a company spends more on advertising, presumably the effect on sales revenue the more sales revenue will be positive, but at the same time, the company tries to minimize costs to maximize profit; thus, we choose efficiency to measure the optimization of costs. Because Data Envelopment Analysis (DEA) does not assume a specific pattern of association among variables, it provides a general picture of the performance of the expenditures (a detailed explanation of DEA is presented in Section III.) We adopt DEA to estimate efficiency scores by entering R&D, SG&A, and COGS as variables to assess how they collectively optimize sales. Then, we explore how efficiency affects deviation between the book value and the market value. We discover that efficiency scores are positively associated with BM, which suggest that efficient companies are, in general, undervalued. Scholars attribute positive association between stock returns and BM to off-balance sheet investment, such as R&D and brand development cost, which generate extra risk and mis-pricing of the stock (Sung *et al.*, 2019; Luo *et al.*, 2014; Zhang 2002). We supply evidence that *efficient* off-balance sheet investment increases BM.

Our study contributes to the literature in at least three ways. First, no prior research has related efficiency to BM. Recent research (Khan and Shireen, 2020; Partalidou *et al.*, 2020; Kwateng, *et al.*, 2019; Tamatam et al., 2019; Sangwan and Choudhary, 2018; Sufian, 2011) reports ways in which companies can enhance operational efficiencies, but no study has documented whether efficient operations affect the divergence between market value and book value. We examine the impact of efficiency on BM, a measure widely used in finance for firms' risk and growth potential. Financial analysts use BM to gauge whether a firm's common stock is overvalued. Our results show that efficiency of off-balance sheet activities can add risk to company's value and be relevant to BM. Second, we include not only R&D, SG&A but also COGS in our model to estimate the efficiency of the pharmaceutical industry. Previous research on the U.S. pharmaceutical industry's efficiency analyzes either R&D efficiency (Shimura *et al*., 2014) or marketing efficiency (Cheong and Kim, 2015), however, we include all three (R&D, SG&A, and COGS) in our DEA model to obtain the overall efficiency of all three important activities. Third, we add to the literature by measuring changes of DEA-calculated efficiencies over time. In doing so, we find companies having relatively smaller levels of assets and higher BM are consistently more efficient than other firms in the U.S. pharmaceutical industry having higher levels of assets and lower BM. Additionally, we find companies that are inefficient overall are inefficient in R&D and SG&A rather than in COGS. Since R&D is long-term investment and the generator of growth, there is limited flexibility to alter the R&D pipeline. We recommend that pharmaceutical companies improve efficiency in SG&A spending.

LITERATURE REVIEW

We calculate BM by dividing the book value of equity by market capitalization (following Fama and French, 1995). BM provides an estimate of the collective market expectation of the stock value. That is, when BM is larger (smaller) than one, the market values the company lower (higher) than the book. Investors can earn extra returns than the average market returns by trading low BM stocks, therefore, stock analysts often use BM as an indicator of potential growth of the company (Hall and Tochterman, 2008). Fama and French (1995) first document that stock returns are positively associated with BM. Capital market scholars since then have been investigating the reason behind the phenomenon. Lev and Sougiannis (1999) report the main reason is that investors demand compensation for the risk on high BM stocks.

The most obvious risk of pharmaceutical industry to investors is R&D expense. U.S. GAAP requires all R&D expenditure be expensed rather than being capitalized until the formula is patented. Therefore, investors may be optimistic about the development of a certain drug, but the value of the drug is not included in the balance sheet (Hulton and Hao, 2008; Chambers, *et al*., 2002). Prior research finds that high (low) R&D investment is associated with low (high) BM (Harrington 2012; Golec and Vernon, 2009; Lev and Sougiannis, 1999). This suggests that when a company invests heavily in R&D, investors tend to overvalue the company (low BM); as R&D results in marketable products, the intangible assets are recognized on the balance sheet, and the company scales back the spending in R&D, and BM increases. If the goal of a company's manager is to achieve short-term growth in stock price, the manager could over-spend in R&D, trying to create an illusion of growth. Hence, whether R&D is spent efficiently should determine the level of BM.

Another expense that can create intangible assets but that is not reported on the balance sheet is marketing expense. The pharmaceutical industry is one of the industries that spend most on advertising and marketing (Swanson 2015). Advertising and marketing expenses can be larger than R&D (Schweitzer and Lu 2018, 270). This is because it takes extra effort to convince customers to accept new products (Chernev, 2018). Advertising and marketing expenditures not only help generate sales revenues but also enhances stock prices. Gu and Li (2006) report that advertising expenses of pharmaceutical companies are highly associated to their stock prices, indicating that investors view advertising and marketing expenditures as beneficial to future value of the firm. In addition, advertising and promotional campaigns help companies strengthen brand image and cultivate customer loyalty, albeit not capitalized on the balance sheet. McAlister *et al*. (2007) conjecture investors would consider marketing expense as an increment to the company value, and they report that larger marketing expenses are associated with lower stock's systematic risk. As investors recognize the benefit of marketing expense, while the book value does not reflect the benefit, marketing expense can be a factor that causes the book value to deviate from market value.

The third expenditure we expect to affect BM is cost of goods sold (COGS). COGS is the largest expense on a pharmaceutical company's income statement. Larger COGS usually is associated with larger sales; however, it is also linked to the higher inventory value on the balance sheet. As the inventory value increases, *ceteris paribus*, book value increases. Nonetheless, the increased value of inventory will reduce revenues via COGS. The market's expected gross profit that ultimately builds up retained earnings should be a cause of divergence between market value and book value.

Despite numerous studies documenting risk arising from R&D, marketing, and supply chain, we lack a general measure for pharmaceutical companies' performance that concludes their critical operational activities. Since Charnes *et al*. (1978) first introduced data envelopment analysis (DEA) to assess efficiencies and production of decision making units (DMU), DEA has been a popular means to evaluate performance of the pharmaceutical industry. For instance, Shimura *et al*. (2014) use DEA to estimate R&D efficiency and find that the less efficient companies are more likely to experience merger and acquisition. Cheong and Kim (2015) apply DEA to evaluate efficiency of advertising in 11 media outlets of U.S. pharmaceutical companies, and they discover that 35% of advertising on network TVs is wasted. Veleva and Cue (2017) report that U.S. generic drug companies do not adopt green chemistry in the manufacturing process as much as big pharmaceutical companies measured by efficiency scores of DEA model. These studies shed light on individual risk areas of the pharmaceutical industry, but how R&D, marketing spending, and inventory costs interact with political and technology shifts remains an open question.

A recent strand of capital market research utilizes DEA to measure managerial ability and to investigate how manager's ability affects the quality of earnings. Demerjian *et al*. (2012) propose a measure of manager's ability by assessing how efficiently managers transform corporate resources (COGS, SG&A, property, plant, and equipment, operating leases, R&D, goodwill, and other intangibles) to sales revenues. They find that stock prices react positively to their so-defined efficient managers, and these managers utilize proceeds from equity issuance effectively. Demerjian *et al*. (2017) continue to use the manager ability matrix to examine the likelihood of income smoothing. They document that high-ability managers are more likely to engage in earnings smoothing, and that smoothed earnings are associated with improved future operating performance. Baik *et al*. (2013) report that changes of operational efficiency are associated with future profitability, however, equity investors do not integrate the information and result in abnormal returns. Baik *et al*. (2020) also discover that high-ability managers' income smoothing improves not only informativeness of earnings but also stock price informativeness about future cash flows. Because the chief interest of this study is the U.S. pharmaceutical industry, we are inclined to evaluate the efficiency in utilizing the largest expenses to generate number of prescriptions, and whether such efficiency influences the distance between book value and market value.

A series of new regulations were passed in the 90's and early 2000's, causing strategic changes in the Indian pharmaceutical markets. Mahajan et al. (2014) use DEA to cope with uncertain impacts of many factors in the Indian pharmaceutical industry. They use raw material cost, salary and wages, advertising and marketing cost, and capital usage cost as input variables, and net sales is the output variable. Out of 50 Indian pharmaceutical companies during 2010 and 2011, Mahajan et al. (2014) identify 19 firms on the efficient frontier. Mahajan et al. (2014) put efficient firms in three categories: efficient in operational costs without size effect, efficient in size effect only, and efficient in both. Their study fails to document the impact of R&D and inventory management, two of the core value-generating activities.

In addition, management prepares financial statements to inform the market the value of the company. The reasons why the market value disagrees with the book value are worth investigating. As the U.S. experienced new regulations recently, and artificial intelligence and machine learning make R&D, marketing, and supply chain management more efficient than before, we are interested in exploring the effect of efficiency from R&D, marketing, and inventory management on the divergence of a pharmaceutical company's book value and market value in the recent decade.

Besides relating efficiency to BM, we build on literature of DEA in the pharmaceutical industry by including sales of total channels by number of prescriptions. Number of prescriptions is a more direct measure than sales revenue to assess R&D and marketing results of pharmaceutical companies, because prescriptions are written by doctors. Pharmaceutical companies report sales revenues after all sorts of discounts and rebates with wholesalers and insurance agents. In addition, when pharmaceutical companies sell rights to their drugs to others, they recognize revenues, but there is not a delivery of drugs (Nurhayati and Choong, 2019). Unlike sales revenue, which is a mixed information of price and quantity, number of prescriptions describes purely the demand of a pharmaceutical company's products. We offer a more precise measure of efficiency to the literature.

We have three objectives for this study: 1) to document how efficiency affects BM; 2) to document the variation of efficiency across the years; 3) to identify the common financial characteristics of efficient companies and make recommendations to inefficient companies.

METHODOLOGY

DEA Model

DEA is a non-parametric method used to measure the relative efficiency of entities or decision- making units that use multiple inputs to produce multiple outputs (Charnes *et al.*, 1978). DEA overcomes the limitations of traditional efficiency measures that rely on a single performance metric. A decision-making unit (DMU) is the unit of analysis in DEA. It can range from a single department to an economy. Each DMU consumes a common set of inputs in the production of a common set of outputs. The underlying assumption is that decision making units consume a common set of inputs in the production of a common set of outputs so that those units exhibiting relatively inefficient performance could be targeted for improvement or change. The goal of DEA is to identify those inefficient units.

In this study, DEA is used to determine the mix of resources that lead to pharmaceutical firms' success and efficiency. Our study uses DEA since DEA has a non-parametric nature and ability to evaluate efficiency in the presence of multiple input and output variables. Input variables represent the resources firms invest in their business operations whereas output variables represent the outcome of such business operations. DEA provides an appropriate fit for the analysis required to address our key research questions in the pharmaceutical industry.

A comprehensive taxonomy and framework of DEA can be found in Das, *et al.* (2018) and Gattoufi *et al*. (2004). According to prior research, the most widely used DEA models are the CCR and BCC models. The CCR and BCC models differ as the CCR model exhibits constant returns to scale and the BCC model exhibits variable returns to scale. The returns to scale concept represents the relationship between the inputs and the outputs when either of them are changed. Returns to scale, also known as elasticity, refers to increasing or decreasing efficiencies based on the size of the change. Constant returns to scale is whereby a change in either the input or output results in a directly proportional change in the other. Variable returns to scale can be either increasing or decreasing. Increasing returns to scale is whereby an increase in input leads to an increase in output in greater proportion than the input increase. Decreasing returns to scale is whereby an increase in input leads to proportionally lower increase in output (Banker- *et al.*1984). The definition of firm efficiency is adopted from Kamakura *et al.* (1988). A company is inefficient if there are some other companies with lower input for equivalent or higher output.

$$\underset{h_j, s_r^+, s_i^-}{(\max)}\, Z_k + \xi\left(\sum_{r=1}^{g} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \tag{1}$$

Subject to:

$$p_{rk} z_k - \sum_{j=1}^{n} p_{rj}\, h_j + s_r^+ = 0 \ \ (r = 1, 2, \dots, g) \tag{2}$$

$$\sum_{j=1}^{n} x_{ij}\, h_i + s_i^- = x_{ik} \ \ (i = 1, 2, \dots, m) \tag{3}$$

$$\sum_{j=1}^{n} h_i = 1 \tag{4}$$

$$h_j, s_r^+, s_i^- \geq 0 \ \ (j = 1, 2, \dots, n)$$

where n is the number of firms included in the sample for each year, m the number of inputs, g the number of outputs, x_{ij} the level of i-type input for company j, p_{rj} the level of r-type output for company j, Z_k is the efficiency ratio for the company under consideration, ξ is a small positive parameter, s_r^+ and s_i^- are slack variables for output r and input i, h_j is the weight for company j. A computer program is utilized to solve the above DEA models for each of the seven years (2009 – 2015) studied. The slacks measure, in addition to the cost reduction, how many more of the attributes should be offered by the inefficient firms to make them efficient (Kamakura et. al, 1988). According to these models, the objective is to reduce the eventual slack in inputs (costs) without reducing the optimal output (technical performance). If, for instance, the input slack is equal to unity, the observed firm is efficient. If, on the other hand, the input slack is less than unity, the firm under investigation is inefficient. A computer program is utilized to solve the above DEA models for each of the years investigated.

Model Specification

In pharmaceutical markets, the firm sets out a budget and aims to maximize the benefits derived from their investment. Based on their distance from the efficiency frontier, firms that are on or that lie closer to the efficiency frontier than other firms are deemed as being relatively more efficient in converting their inputs to outputs. A firm is deemed as being inefficient if another firm can produce the same amount of output by using less input or alternatively if another firm can use the same level of input and produce a higher level of output.

Input and Output Variable Selection

To run the DEA model, we use R&D expense (R&D), selling and general administrative expense (SG&A) and cost of goods sold (COGS) as input variables; and we use sales of all channels (Sales_Dollar) and sales by prescriptions (Sales_TRx) as output variables. One limitation of DEA is the potential problem of differentiating DMUs, which can either be caused by an excessive number of input and output variables with respect to the total number of DMUs in the analysis, or the use of highly correlated input and output variables (Adler and Berechman, 2001). The utility of DEA depends on its ability to calculate the relative efficiency of DMUs using multiple inputs and outputs. However, the greater the number of input and output variables, the less discerning the analysis is. This does not portray a realistic picture of the pharmaceutical markets as it implies that a large percentage of firms in the industry are operating at full efficiency (Jenkins and Anderson, 2003). To overcome the limited distinction provided by DEA due to highly correlated variables, some studies have taken the approach of retaining only those that are perceived as being more important in an ad-hoc manner.

Regression Model and Variables

We use regression model to examine the association between efficiency and BM.

$$BM_t = \beta_0 + \beta_1 EFFICIENCY_t + \beta_2 LOG\ ASSETS_t + \beta_3 ROE_t + \beta_4 DVT_t + \beta_5 MA\ DUMMY_t + \beta_6 FOREIGN_t + \varepsilon_t \tag{5}$$

In addition to our key variables, BM and Efficiency, we include several control variables to ensure the association. Prior literature documents that size of the company is positively associated with BM (De Carolis, 2003), and we use natural log of total assets (LOG_ASSETS) as the proxy for company size. We also include return on equity (ROE), because investors typically overvalue the stock when the company is profitable (Beaver and Ryan, 2000). Previous research documents that the market penalizes companies that do not continue to pay dividends (Healy and Palepu, 1988). Therefore, we expect the market to overvalue the company when the company pays dividends (DVT). Pharmaceutical companies frequently merge or acquire other companies in order to improve their drug pipelines, therefore, we expect investors to be optimistic about a merger (MA_DUMMY) and overvalue the company (Maksimovic and Phillips, 2001). Investors can be positive about the company's future when the company has foreign operations (Bodnar and Weintrop, 1997). We use dummy variable FOREIGN to surrogate foreign operations and expect FOREIGN to be negatively associated with BM. Detailed formation of variables is described in Appendix.

Data

Financial data of pharmaceutical companies from 2009 to 2015 are downloaded from COMPUSTAT database. We then merge financial data with IQVIA's (then IMS Health's) sales data. IQVIA's sales data are summed by all distribution channels and are stated as dollars as well as number of prescriptions. The merged sample results in 188 firm-years of data, separated into 7 years (2009 to 2015) of tables. TABLE 1 shows that our observations gradually increase from 12 percent to 18 percent in the sample period. Because more than 60 percent of our observations are after 2011, we believe our sample firms are not significantly affected by the financial crisis in 2008.

TABLE 1
YEAR DISTRIBUTION

Fiscal Year	Number of Observations	Percentage %
2009	22	11.70
2010	23	12.23
2011	26	13.83
2012	24	12.77
2013	28	14.89
2014	31	16.49
2015	34	18.09
Total	188	100.00

TABLE 2 illustrates the statistics of our test variables. The average efficiency score is 0.367. The low efficiency score means our method of estimating efficiency is able to distinguish efficient companies from inefficient ones. Our main variable, BM, is on average 0.306. While BM ranges from -0.724 to 1.676, 75 percent of observations have BM not larger than 0.406, suggesting that most of our companies in a year are over-valued. We use total assets as the proxy for company size. The average total assets of our companies per year is $36,104 million, but they vary from $5 million to $167 billion. Return on equity (ROE) is 0.163, even though maximum of ROE is 11.676, 75 percent of observations have ROE of 0.266 or lower. Our sample companies pay $1,408 million of dividends (DVT) on average, but only 25 percent of them pay dividends in a year. 45.2 percent of companies experience merger and acquisition (MA DUMMY) in a year, and 64.4 percent of companies has international operations (FOREIGN).

TABLE 2
DESCRIPTIVE STATISTICS (N=188)

Variable	Mean	Std. Dev.	Min.	Med.	Max.
EFFICIENCY	0.367	0.322	0	0.276	1
BM	0.306	0.242	(0.724)	0.267	1.676
Total Assets	36,104	48,082	5	14,985	167,460
ROE	0.163	0.992	(2.542)	0.169	11.676
DVT	1,408	2,281	0	0	8,173
MA_DUMMY	0.452	0.499	0	0	1
FOREIGN	0.644	0.480	0	1	1

Total assets in millions of dollars

We report correlation between variables as TABLE 3. Efficiency is positively correlated with BM (0.293), suggesting that more efficient companies are under-valued. Size of the company (LOG_ASSETS) is not correlated with BM. However, size of the company is negatively correlated with efficiency (-0.332). Smaller companies appear to be more efficient than larger companies. Additionally, larger companies are more likely to engage in merger and acquisition (0.435), have foreign operations (0.477) and pay dividends (0.714). Profitability of the company (ROE) is negatively correlated with BM, indicating that profitable companies are over-valued. While merger and acquisition (MA_DUMMY) affects investor's perception of the company's future, the change of market value may be offset by the change of book value after the combination, therefore, we do not see correlation between MA_DUMMY and BM. Foreign operations (FOREIGN) is negatively correlated with BM (-0.204), meaning investors over value companies who have global presence. At the same time, companies with foreign operations are less efficient (-0.200). This may explain why larger companies are less efficient, since foreign operations are more complex and more difficult to manage. Although the market responds to dividends payment (DVT), market value would not deviate much from book value as DVT is not correlated with BM. The matrix shows that DVT is negatively correlated with efficiency (-0.331). We suspect that dividends could have been reinvested to operations such as marketing and R&D to enhance sales. Besides size of the company, dividends payment is also positively correlated with MA Dummy (0.349) and FOREIGN (0.205). Since large companies often have merger and acquisitions, and they usually have foreign operations, it is not surprising to find these companies to pay dividends.

TABLE 3
PEARSON CORRELATION

	BM	EFFICIENCY	LOG_ASSETS	ROE	MA_DUMMY	FOREIGN
Efficiency	**0.293**					
LOG_ASSETS	-0.094	**-0.332**				
ROE	**-0.325**	-0.081	0.010			
MA_DUMMY	0.057	-0.094	**0.435**	0.072		
FOREIGN	**-0.204**	**-0.200**	**0.477**	0.009	0.163	
DVT	0.012	**-0.331**	**0.714**	0.091	**0.349**	**0.205**

Correlation with p-value<0.05 is bolded.

We are interested in the influence of efficiency on the under or over-valuation of pharmaceutical companies, therefore, we dissect the sample into companies that are less efficient versus the ones that are more efficient. Companies whose efficiency score is less than mean of the sample (0.367) are in the “less efficient” group, and companies with efficiency score equal to or larger than the mean are in the “more efficient” group. TABLE 4 exhibits the differences in variables between the two groups. We find that less efficient companies have lower BM than more efficient companies. Consistent with Pearson Correlation reported in TABLE 3, more efficient companies are generally under-valued. More efficient companies possess smaller assets than less efficient companies. This is intuitive since, by definition, efficient companies can reach the same outcome as the others with fewer resources. Profitability (ROE) and merger and acquisition activities (MA_DUMMY) do not vary much between more efficient and less efficient companies. Baik et al. (2013) find profitability is positively associated with efficiency scores, and we attribute our insignificant difference of profitability between efficient and inefficient companies to the different sample companies we retrieved. Baik et al. (2013) retrieve company’s return on net operating assets (RNOA) across all industries from 1976 to 2008, whereas we download return on equity (ROE) of only pharmaceutical companies from 2009 to 2015. Since we are interested in how efficiency affects BM, the insignificant correlation between ROE and efficiency scores does not impede our primary finding and is of less concern in this study. Similar to the notion from the correlation matrix, more efficient companies are less likely to have foreign operations and pay less dividends than less efficient companies.

TABLE 4
DIFFERENCE BETWEEN LESS EFFICIENT AND MORE EFFICIENT COMPANIES

	Less Efficient (n=107)				More Efficient (n=81)				Less - More		
Variable	**Mean**	**Std Dev**	**Min.**	**Max**	**Mean**	**Std Dev**	**Min.**	**Max.**	**Mean**	**t**	
EFFICIENCY	0.13	0.10	0.00	0.36	0.68	0.22	0.37	1	-0.557	-20.8	***
BM	0.27	0.18	-0.72	0.64	0.36	0.30	0.02	1.68	-0.096	-2.57	**
Total Assets	51,245	54,130	5	167,460	16,104	28,461	71	167,460	35,140	5.75	***
ROE	0.23	1.22	-2.51	11.68	0.08	0.57	-2.54	1.81	0.146	1.09	
MA_DUMMY	0.50	0.40	0	1	0.40	0.49	0	1	0.100	1.37	
FOREIGN	0.71	0.46	0	1	0.56	0.50	0	1	0.155	2.21	**
DVT	2,178	2,659	0	8,173	391	977	0	4,918	1,787	6.41	***

RESULTS

The regression result of efficiency on BM is reported in Table V. Efficiency is positively associated with BM, which supports our expectation that efficient companies are under-valued by investors. We do not find evidence that size (LOG_ASSETS) of the company is associated with BM. ROE is significantly negatively associated with BM, suggesting that more profitable stocks are more over-valued. While we expect investors' perception of the firm value to deviate from book values when the company engages in merger and acquisitions (MA_DUMMY) and when the company operates globally (FOREIGN), we do not find evidence that MA_DUMMY to be related to BM. On the other hand, we find that foreign operations are negatively associated with BM, indicating that investors tend to over value companies who have foreign operations. Dividends payment (DVT) is positively associated with BM. This implies that companies who pay dividends tend to be undervalued. Our model has high explanatory power (Adjusted R-square 0.138), and untabulated analysis of Variance Inflation Factor (VIF) shows that all variables have VIF lower than 3.0, which assures us that our model is not subjected to multi-collinearity issue.

TABLE 5
REGRESSION OF EFFICIENCY ON BOOK-TO-MARKET RATIO

Variable	Expected Sign	Coefficient	t-value	
EFFICIENCY	+	0.206	4.07	***
LOG_ASSETS	+	-0.006	-0.59	
ROE	-	-0.075	-2.59	**
MA Dummy	-	0.042	1.22	
FOEIGN	-	-0.072	-1.94	*
DVT	-	0.000	2.01	**
Intercept		0.285	4.16	***
n		188		
Adj. R-square		0.138		

ADDITIONAL TESTS

The regression analysis shows that efficiency in critical expenses of pharmaceutical companies significantly contributes to the undervalue of the stock. We then are interested in exploring how the efficiency scores vary year by year and identify the characteristics that sustain firms' efficiency in the long run. We also perform slack analysis to seek the most relevant expenditure to the efficiency score.

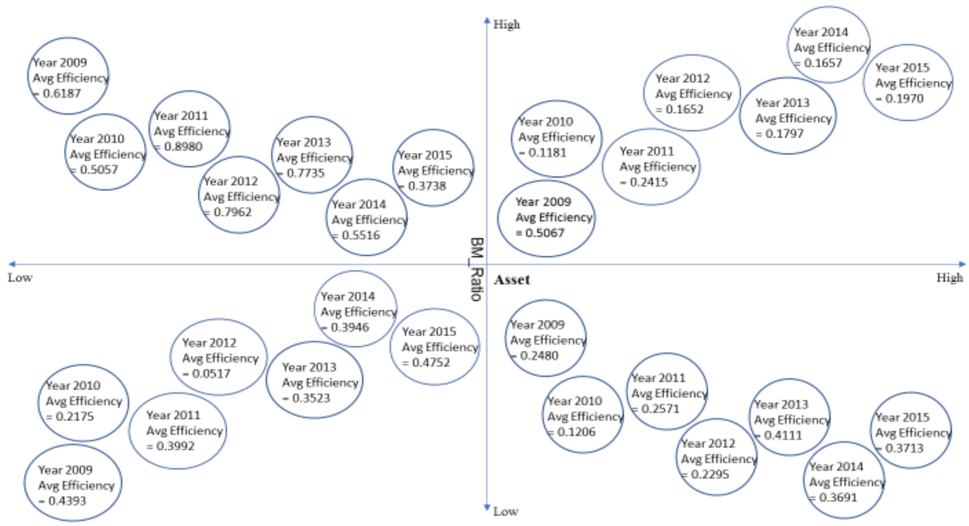
Longitudinal Analysis

As shown in FIGURE 1, in 2009, the average of efficiency is highest at 0.6187 for the firms with low assets and high BM ratio, while the firms in the quadrant of high assets and low BM ratio have the lowest average of efficiency at 0.2480. In 2010, the average of efficiency is lower in all the four quadrants compared to the corresponding averages in the prior year. Again, the firms with low assets and high BM ratio perform better than firms in other three quadrants. The firms with high assets and high BM ratio have the lowest efficiency score in 2010.

In 2011, the average of efficiency has increased in all the four quadrants compared to the year of 2010. The average in the quadrant of low asset and high BM ratio has reached 0.8980, indicating firms in this category can only reduce their inputs by 10.2 percent of their observed levels without affecting output levels. In 2012, the year after, the pattern continues in that firms with low assets and high BM perform the best. The most noteworthy in 2012 is that the firms in the quadrant of low asset and low BM ratio have an average of efficiency of 0.0517, the lowest.

In 2013 and 2014, again, the firms with low asset and high BM ratio perform better than firms in the other three quadrants. The firms with high assets and high BM ratio have the lowest efficiency scores. This pattern is very similar to that in 2010. Another year worthy of our attention is 2015, in which a different patten is observed. The highest average of efficiency falls in the category of firms with low assets and low BM ratio. However, this “highest” average is much lower than the highest ones found in previous years.

FIGURE 1
LONGITUDINAL



Slack Analysis

Slacks in inputs are calculated to show how those inefficient firms can reduce their inputs to become efficient while keeping the same outputs. In 2009, 2011, 2013, 2014 and 2015, the correlation between R&D and efficiency score is significantly positive, but the correlation is not significant between SG&A and the efficiency score. In 2010 and 2012, the correlation is neither significant between SG&A and the efficiency score nor significant between R&D and the efficiency score.

For the results in TABLE 6, we observe that in 2010, there are fourteen firms having slack in both R&D and SG&A, ten having slack only in R&D and nine firms having slack only in COGS. No firm has slack only in SG&A in 2010. A significant amount of slacks in inputs for these firms indicates big room for improvement on utilizing inputs more efficiently. In 2009, 17 firms have slacks only in R&D, which shows these firms can reduce their R&D investment to become efficient. In 2011, the number of such firms increases to 21, which means most inefficient firms with efficient score less than one may reduce R&D to operate on the efficient frontier. Similar conclusion can also be drawn for seventeen, sixteen and eighteen inefficient firms in 2012, 2013, and 2014 respectively. 2015 is different with only eight firms having slack in R&D only, but 16 firms have slack in SG&A only. In 2013, not only 16 firms have slacks in R&D only, there are ten firms having slacks in SG&A only as well.

In 2009, 2010, and 2012, most inefficient firms have slack only in R&D. It implies the R&D investment isn’t efficiently transformed into the comparable outputs. Stated differently, these firms could have spent less R&D to generate their existing outputs.

The number of firms having the slacks pertaining to COGS is far lower than that having slacks in R&D and SG&A. Therefore, efficient R&D and SG&A is needed to maximize sales for those inefficient firms. The reduction of R&D is difficult since it is usually invested to accomplish a long-term strategic goal. Cutting SG&A, on the other hand, is more likely to maintain the output level without sacrificing long-term growth. For example, digital channels to market drugs can make SG&A more efficiently.

TABLE 6
SLACK ANALYSIS ON R&D AND SG&A

Number of firms having slacks in the listed input(s)	2009	2010	2011	2012	2013	2014	2015
Both R&D and SG&A	4	14	1	1	0	1	4
R&D Only	17	10	21	17	16	18	8
SG&A Only	1	0	9	0	10	5	16
COGS	1	9	1	4	6	7	7

CONCLUSION

In this paper, we use data envelopment analysis to explore how efficiencies of U.S. pharmaceutical companies affect book-to-market ratio (BM) from 2009 to 2015. U.S. pharmaceutical industry experienced significant regulatory and technological changes during this period, and no studies have investigated the influence of efficient operations on the divergence between book value and market value after these macroeconomic shocks. We find that operational efficiency is positively correlated with BM, meaning that companies who spend efficiently in R&D, marketing, and inventory costs are generally undervalued. The average efficiency scores have fluctuated from year to year, but the efficient companies constantly are smaller (low assets) and more undervalued (high BM). In addition, slack analysis suggests that inefficient companies are generally inefficient in R&D and SG&A. Because R&D projects usually are for company's long-term growth, we recommend companies to improve efficiency in SG&A.

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APPENDIX: VARIABLE DEFINITION

Variable	Definition	Source
BM	Book-to-market ratio	COMPUSTAT: $\frac{Total\ assets\ (AT) - Total\ liabilities (LT)}{Closing\ price\ at\ the\ end\ of\ the\ fiscal\ year\ (PRCCF) * Common\ Shares\ Outstanding}$
COGS	Cost of goods sold	COMPUSTAT: Cost of goods sold (COGS).
DVT	Dividends	COMPUSTAT: Total dividends (DVT).
EFFICIENCY	Efficiency score	Efficiency score estimated by DEA using Sales_Dollar and Sales_TRx as output variables and XRD, XSGA, and COGS as input variables.
FOREIGN	Foreign operations	COMPUSTAT: 1 if the company reports foreign currency transaction (FCA).
LOG_ASSETS	Total assets	COMPUSTAT: Natural log of total assets in millions of dollars (AT).
MA_DUMMY	Merger and acquisition	COMPUSTAT: 1 if the company reports merger and acquisition transaction (AQP).
Sales_TRx	Sales by prescriptions	IQVIA: total sales of all channels by prescriptions
Sales_Dollar	Sales by dollars	IQVIA: total sales of all channels by dollars

R&D	Research and development expense	COMPUSTAT: Research and development expense (XRD).
SG&A	Selling, general, and administrative expense	COMPUSTAT: Selling, general, and administrative expense (XSGA).