DO INVESTORS VALUE FIRM EFFICIENCY IMPROVEMENT? EVIDENCE FROM THE AUSTRALIAN CONTEXT

Hai Yen Pham*, Richard Chung*, Eduardo Roca*, Ben-Hsien Bao**

*Griffith University, Australia
**The Hong Kong Polytechnic University, Hong Kong SAR, China

Abstract

Do investors value improvement in efficiency? This paper investigates the relation between the firm's technical efficiency change and subsequent stock returns. We employ a stochastic frontier analysis to evaluate a firm's efficiency for a large panel of non-financial companies in Australia from January 1990 to October 2012. The results show that over the sample period, the estimated mean improvement in firm's efficiency is 3% per year. We find that an equally-weighted (value-weighted) portfolio of stocks with the top tertile level change in efficiency outperforms an equally-weighted (value-weighted) portfolio of stocks with the bottom tertile level change in efficiency, by an average of 11% (7%) per annum during the sample period. We also find a significant efficiency change effect on a cross-section of stock returns after controlling for other risk factors such as size, book-to-market, market liquidity, industry concentration, and seasonality effect.

Keywords: Efficiency change · Stock returns · Stochastic frontier analysis
JEL classification: G11, G12

1. INTRODUCTION

The productivity or efficiency of an organization is its ability to transform inputs such as labor and capital into outputs such as goods and services (Australian Bureau of Statistics, 2012). At the macro-economic level, productivity refers to the efficiency with which an economy employs resources to produce economic output. For a given set of inputs, the higher the productive efficiency, the higher the output that can be produced. Therefore, growth in productivity is viewed as the key driver of growth in per capita income and living standards in the long run (D'Arcy and Gustafsson, 2013). Productivity growth is also important to the firm so it can meet its obligations to workers, shareholders and governments and still remain competitive or even improve its competitiveness in the marketplace (Parham and Economics, 2013). When discussing the importance of productivity growth, Nobel Prize-winning economist Paul Krugman said: "Productivity isn't everything, but in the long run, it is almost everything".

One good indicator of productivity is multifactor productivity, which is the quantity of value added obtained from a 'unit bundle' of both labor and capital (Australia's Productivity Performance, 2009). Multifactor productivity growth can be decomposed into two growth factors: technological progress in the long term, which represents improvements in ways of doing things, and technical efficiency growth in the short term, which reflects unexplained factors such as cyclical variations in labor and capital utilization, economies of scale and others (Australian Bureau of Statistics, 2012). In this paper, we focus on the relation between short-term change in technical efficiency and future stock returns.

Over the last four decades, the growth in multifactor productivity accounted for over one-third of the growth in Australia's real incomes (Australia's Productivity Performance, 2009). Recently, however, as indicated in the Australian government's reports, Australia's productivity growth has fallen from 0.7% per year in the period 1998-2004 to a negative number of -0.8% per year in the period 2005-2008 (Australian Bureau of Statistics, 2012). Thanks to the commodity boom and terms of trade boost in recent years, that performance has been masked; however, there is the likelihood that Australia's terms of trade will decrease as the commodity price cycle runs its course (Green, Toner and Agarwal, 2012). In addition, given its aging population, the participation of the population in the labor force will decrease in the future. Hence, the need to improve Australia's productivity performance is undoubtedly in the national interest. However, do investors value improvement in firm efficiency? This question motivated us to study productivity or efficiency; in particular, we investigate how the change or growth in a firm's technical efficiency contributes to the growth of investors' future wealth in the context of Australia.

Classical finance theory argues that there is a trade-off between risk exposures and asset return. Riskier assets have more uncertain outcomes, and when investors are risk averse, they will demand a premium for holding such assets (Frijns, Margaritis and Psillaki, 2012). The Capital Asset Pricing Model (CAPM), which was introduced by Sharpe (1964), Lintner (1965) and Black (1972), states that there is a linear relation between beta (systematic risk) and expected stock returns and that beta is sufficient to explain the variation in expected returns. However, the empirical evidence suggests the existence of other factors not captured by beta that can explain the variation in future stock returns such as size and book-to-market (Fama and French, 1992), momentums (Jegadeesh and Titman, 1997), excess cash holding (Dittmar and Marhrt-Smith, 2007), liquidity (Chan and Faff, 2003; Mahipala, Chan and Faff, 2009), default risk (Garlappi, Shu and Yan, 2008), industry concentration (Hou and Robinson, 2006) and corporate governance (Gompers, Ishii and Metrick, 2003).

Firm technical efficiency refers to how much output (i.e., sales and firm value) can be obtained given a set of inputs such as a firm's labor, plants, properties, equipment, managerial strengths and investment choices (Nguyen and Swanson, 2009), which may play an important role in asset pricing (Frijns et al., 2012). Many prior studies that rely on alternative performance measures emphasize that efficient frontier approaches seem to be superior to traditional financial ratios (Berger and Humphrey, 1997; Gaganis, Hasan and Pasiouras, 2013) and are more likely to be incrementally informative than those mandated by regulation (Kothari, 2001). However, these studies' findings on the relation between firm efficiency level and stock returns are far from a consensus: some have documented that firm efficiency is negatively related to stock returns (Nguyen and Swanson, 2009), whereas others have found a positive relation between them (Alam and Sickles, 1998; Frijns et al., 2012).

Similar to Amess and Girma (2009), we suggest that a firm's shareholders are more concerned with the change in firm efficiency than the firm efficiency level itself. Shareholders value organizational improvements and the adoption of better management practices that lead to better resource utilization rather than the level of efficiency (Amess and Girma, 2009). In addition, compared to the efficiency level, the change in firm efficiency not only provides information regarding firms' abilities to remain or improve their profits relative to their peers but also offers information about the trend of firms' future performance.

More practically, in the context of the urgent call within Australia for improving the efficiency and productivity of its industries and businesses, does improvement in efficiency lead to higher stock returns? Of course, the results of this study would also be very useful to financial market participants such as firm's shareholders, investors, fund managers, financial advisors, and others because compared to traditional financial indicators, the efficiency measurement approach appears to be superior, offering more information regarding firms' competitiveness (Berger and Humphrey, 1997; Kothari, 2001; Gaganis et al., 2013).

Academically, our study contributes to the existing literature in a number of ways. First, there are now a large number of studies examining the effect of a change in firm efficiency on stock returns in the US; however, this issue remains relatively unexplored in Australia. There are some studies on the issue of efficiency related to banking and insurance in Australia (see Kirkwood and Nahm, 2006; Shamsuddin and Xiang, 2012), but these studies do not investigate the impact of efficiency change on future stock returns and none of them address non-financial firms. Therefore, our study attempts to fill this gap. Second, this research uses a large sample consisting of most listed non-financial companies during the period from January 1990 to October 2012. The sample is representative of all non-financial industry sectors in the Australian Securities Exchange (ASX), thus, the findings are generalizable to the population of listed non-financial companies. Finally, our study provides a more comprehensive analysis, as it investigates the relation between firm efficiency change and stock returns over time and across industries. The seasonality effect in Australia is taken into account as well.

The research proceeds as follows. In the first stage, we estimate firm efficiency level and its change. In the second stage, we examine the impact of changes in firm efficiency on subsequent stock returns. Following Habib and Ljungqvist (2005), efficiency is estimated by comparing a benchmark Tobin's Q of a hypothetical value-maximizing firm to the firm's actual Tobin's Q using the stochastic frontier analysis. Efficiency change is measured as level change or percentage change in efficiency in the current year compared to that in the previous year. The results indicate that the estimated efficiency score of the average firm is approximately 61.5% and that this score has improved 3% per annum over the sample period[3]. The relation between efficiency improvement and returns is examined in both time-series and cross-sectional settings. First, we sort stocks based on efficiency change to construct tertile portfolios and apply the Carhart (1997) 4-factor model of stock returns on those portfolios. Second, we perform the Fama-MacBeth (1973) regression model to determine whether efficiency improvement plays a role in explaining the variance in the cross-section of stock returns. Furthermore, regressions are run by industry to determine the impact of efficiency improvement on future stock returns across industries.

We find that an equally-weighted (value-weighted) portfolio of stocks with a high efficiency change outperforms an equally-weighted (value-weighted) portfolio of stocks with a low efficiency change by an average of 11% (7%) per year. In cross-sectional analysis, the efficiency change helps explain variation in the cross-section of stock returns, even after controlling for known risk factors such as size, book-to-market, market liquidity and industry concentration. Furthermore, the cross-sectional regression results by industry reveal that the efficiency change has power in explaining stock returns in several industries such as materials (mining), industrials, consumer discretionary, consumer staples, health care and utilities.

The remainder of the paper is organized as follows: A brief relevant literature review is presented in section 2, while section 3 describes the methodology. The data are presented in section 4. Section 5 discusses empirical results and the robustness test. Section 6 concludes the paper.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1. Literature review

One of the first studies in this area is that of Alam and Sickles (1998). Data Envelopment Analysis (DEA) was employed on the data of 11 US airlines observed quarterly during the period 1970-1990 to analyze the association between stock market returns and

[3] Similar to the trend in productivity growth in Australia, the percentage change in efficiency of firms in the sample has increased by an average of 5.27% pa during the period 1998–2004, but it has declined by an average of 4.54% pa during the period 2005–2008 and then has improved again by an average of 10.24% pa from 2009 to 2011.

relative technical efficiency. They found a positive relation between efficiency news in a quarter and stock market performance during the following two months. Similarly, Frijin et al. (2012) apply the same technique, namely DEA, on various input/output combinations, focusing on sales and market value as output measures in constructing the frontier technologies for the publicly listed companies in the US during the period 1988-2003. They document that firm efficiency plays an important role in asset pricing and that efficient firms significantly outperform inefficient firms even after controlling for known risk factors.

In contrast, Nguyen and Swanson (2009)—using a stochastic frontier approach to evaluate the firm efficiency of publicly listed firms in the US from 1988 to 2002—report that the portfolio composed of highly efficient firms significantly underperforms the portfolio composed of inefficient firms, even after adjusting for firm characteristics and risk factors, which suggests that investors require a premium for the inefficient firms. Furthermore, they find that the difference in performance between the two portfolios remains for at least five years after the portfolio formation year. In addition, firm efficiency exhibits significant explanatory power for equity returns in a cross-sectional analysis.

With respect to efficiency change, Kirkwood and Nahm (2006), using DEA to evaluate the cost and profit efficiency of Australian banks from 1995-2002, have documented that change in profit efficiency is positively related to contemporaneous stock returns. Amess and Girma (2009) employed both DEA and SFA approaches for a sample of an unbalanced panel of 706 public limited companies observed over the period 1996-2002 in the US. They find a positive relationship between efficiency and the market value of manufacturing sector firms, controlling for traditional accounting measures of performance such as earnings per share and return on capital employed. By contrast, they find no evidence for such a relation in the service sector firms. Gaganis et al. (2013), using a sample of 399 listed insurance firms in 52 countries during the period 2002-2008, find a positive and statistically significant relation between profit efficiency change and market-adjusted stock returns. Hence, given the mixed evidence in the literature, our study examines the relation between improvement in efficiency and future stock returns for Australian non-financial companies.

2.2. Theoretical framework and hypothesis

The notion that a firm's value should be maximized through efficient operation is central for corporate managers. Yet, the empirical evidence suggests that most firms are operated inefficiently for various reasons such as agency cost or financial distress (Chung, Fung and Hung, 2012). Jensen and Meckling (1976) argue that the agency cost is generated by the separation between ownership and control. They postulate that agency cost prevents firms from operating efficiently and from maximizing values due to a firm's management's perquisite consumption, shirking behavior and investing in sub-optimal projects that are not in the best interest of shareholders. Similar to Gompers et al. (2003), we suggest that a decrease (an increase) in a firm's efficiency would cause higher (lower) agency costs in the subsequent year. If investors underestimate (overestimate) these costs and risk, then the firm's operating performance would be worse (better) than expected. This also implies that the firm's value at the beginning of the period would be too high (low) or that the firm is overvalued (undervalued). Consequently, when stock price moves to its intrinsic value, subsequent stock prices and future returns should be lower (higher) than expected.

An alternative explanation regarding the relation between change in efficiency and stock returns comes from Q-theory (Lovell, 1993; Zhang, 2006; Amess and Girma, 2009; Hirshleifer, Hsu and Li, 2013). This theory posits that all other things being equal, firms with higher profitability will have higher stock returns. By taking actions such as providing managers with the appropriate set of incentives, employing better managerial and organizational practices, adopting an efficient monitoring system and so forth, firms improve their efficiency. This improvement in efficiency means firms better utilize their resources—with a given set of inputs, they can produce more outputs or use lower input costs to produce a given set of outputs compared to their peers—and will thus generate better future financial results. Hence, the improvement in efficiency should lead to a better operating performance, higher market valuation and, thus, higher stock returns. Given the above discussion, we therefore hypothesize that there is a positive relation between efficiency change and subsequent stock returns.

3. METHODOLOGY

3.1. Frontier construction

Firm technical efficiency is referred to as the ability to transform inputs to outputs or how much output can be obtained from a given set of inputs. The two most popular methods to estimate firm efficiency are the following: 1) stochastic frontier analysis (SFA), which is parametric; and 2) data envelopment analysis (DEA), which is non-parametric. These two methods have been chosen fairly often by academics, professionals and practitioners, and each method has its own advantages and disadvantages.

DEA is a non-parametric method that is based on mathematical programming. The main advantage of DEA is that it is quite simple, as only input and output information is required. In addition, it does not require any assumption to be made about the distribution of inefficiency or a particular functional form of the data in establishing the most efficient firms (Gaganis et al., 2013). However, when constructing the production frontier line, DEA does not take into account stochastic noise in data representing effects that cannot be controlled by firms such as changes in regulations, worker conflicts, bad weather and measurement errors (Hjalmarsson, Kumbhakar and Heshmati, 1996). Efficiency is measured relative to the highest observed performance rather than an average (Hjalmarsson and Veiderpass, 1992), so its analysis is sensitive to outliers. Additionally, it assumes that data are free of measurement error (Gaganis et al., 2013).

In contrast, SFA's main weaknesses are that it requires an explicit imposition of a particular parametric functional form representing the underlying technology and an explicit distributional assumption for the inefficiency terms (Hjalmarsson et al., 1996). The strength of SFA is that it considers stochastic noise in data and controls for firm characteristics and growth opportunities, and thus, a firm's hypothetical maximum value is estimated from its own characteristics. DEA estimates a true upper bound, whereas SFA is based on a conditional mean rather than enveloping it so outliers do not cause estimation bias. Given their strengths and weaknesses, the choice between the different methods must be based on a trade-off concerning technology characteristics, type of data, quality of data and other factors. As the SFA model offers a richer specification and allows for a formal statistical testing of hypotheses (Hjalmarsson et al., 1996), we therefore choose to use this approach in this study.

Tobin's Q, which is defined as the ratio of the market value of debt and equity to the replacement cost of the firm's assets in place, is used as the output measure in the frontier model. Habib and Ljungqvist (2005) argue that Tobin's Q can be used as a proxy for firm value because if a firm operates and invests in assets that are expected to create added value, then its Q will be greater than 1; the more value created, the higher is the Q. Factors representing firm characteristics and growth opportunities are selected based on prior empirical research on firm efficiency.

Following Habib and Ljungqvist (2005) (In the Habib and Ljungqvist (2005) model, the square of ln(sales) and the square of PPE/Sales are included, but in our model, they are highly correlated to ln(sales) and PPE/Sales, respectively, so we leave them out. The correlation matrix and results of the frontier model using the square of ln(sales) and the square of PPE/sales are available from the authors.), using Tobin's Q as the dependent variable, the stochastic frontier function is estimated as follows:

$$Q_{i,t} = \alpha_0 + \beta_1 * \ln(sales_{i,t}) + \beta_2 * \frac{R\&D_{i,t}}{PPE_{i,t}} + \beta_3 * \frac{CAPEX_{i,t}}{PPE_{i,t}} + \beta_4 * \frac{INC_{i,t}}{sales_{i,t}} + \beta_5 * \frac{PPE_{i,t}}{sales_{i,t}} + \beta_6 * LEV + \beta_7 * FOLL + v_{i,t} - u_{i,t} \quad (1)$$

• Where Q is Tobin's Q of the firm, measured as the ratio of market value of equity plus book value of total debts to book value of total assets.

• $\ln(sales)$ is the natural logarithm of gross sales. Diminishing returns suggest that the average Q will decrease as firms become larger. $\ln(sales)$ is therefore expected to be negatively related to Q.

• R&D/PPE is the ratio of research and development expenditures to net of property, plant, and equipment (PPE), referred to as "soft" spending. Capex/PPE is the ratio of capital expenditures to PPE, referred to as "hard" spending. Both of them proxy for firm growth opportunities and are expected to be positively related to the firm's Tobin's Q.

• The operating margin INC/sales is a measure of the firm's profitability and is computed as the ratio of operating income before depreciation and amortization to gross sales. It is expected to be positively related to the firm's Tobin's Q.

• PPE/sales is the ratio of PPE divided by gross sales. According to Habib and Ljungqvist (2005), it can be positively or negatively related to the firm's value.

• LEV is the firm leverage, measured as the ratio of book value of long-term debt to the sum of market value of equity and book value of long-term debt. The effect of Lev on Q is ambiguous.

• FOLL is a dummy variable that proxies for analyst following and takes the value of unity if the firm is followed by an analyst(s) and 0 otherwise. Financial analysts, by acting as significant information intermediaries between managers, can potentially improve capital markets' information quality. Therefore, we expect that analyst following has a positive effect on Tobin's Q.

• u_i is a one-sided error term greater than or equal to 0. For the firm that lies on the frontier line, u_i=0. In contrast, u_i>0 implies that the firm lies below the frontier line and operates inefficiently. We assume that $\text{cov}(u_i, v_i) = 0$ to assure that the two error terms are independent and uncorrelated; v_i is a two-sided error term in the conventional ordinary least square (OLS) with a normal distribution, including zero-mean, symmetric, independent, and identically distributed error (Chung et al., 2012).

The equation below specifies the normalization procedure to calculate firm efficiency:

$$\text{Efficiency}_i = 1 - \frac{u}{Q^*} = \frac{Q}{Q^*} \quad (2)$$

where Q^* is the hypothetically best-performing value and Q is the actual value for the firm. The shortfall from the frontier, u=Q* - Q, is a measure of inefficiency (Habib and Ljungqvist, 2005). The efficiency score is a normalized measure between 0 and 1. For instance, a score of 0.70 implies that the firm is valued at a 70% level in comparison with its best-performing peers, ceteris paribus. Similar to Nguyen and Swanson (2009), assuming that investors make investment decisions based on the current efficiency level (current information), we compute our efficiency score across firms in each year. In this study, we use both level change and percentage change in firm efficiency. They are defined as follows:

Level change:

$$CH = \mathbf{Efficiency_t - Efficiency_{t-1}} \quad (3)$$

Percentage change:

$$\%CH = \mathbf{(Efficiency_t - Efficiency_{t-1}) / Efficiency_{t-1}} \quad (4)$$

where Efficiency_t is the firm's efficiency in year t.

3.2. Return models

First, we examine the relation between efficiency change and stock returns over time by constructing portfolios based on efficiency change (CH-sorted or %CH-sorted portfolios). Then, we use the Carhart (1997) 4-factor model to test whether there is an abnormal return after controlling for some known risk factors such as systematic risk, size, value and momentum. Second, in terms of the cross-section of returns, we apply the Fama-Macbeth (1973) approach in cross-sectional analysis to test whether efficiency change can help explain the variation in the cross-section of stock returns.

3.2.1. Portfolio construction

In December of each year, *t*, from 1990 to 2012, we rank all stocks in the sample by the efficiency change in ascending order. We then assign stocks into tertile portfolios. The first portfolio (Low) consists of firms with low change in efficiency, the second is Middle, and the last portfolio (High) consists of firms with high change in efficiency. All portfolios are rebalanced at the end of each year.

The Carhart (1997) model, also known as the 4-factor model, is an extension of the Fama and French (1993) 3-factor model (Nguyen and Swanson, 2009). According to the model, in the absence of abnormal performance (i.e., Jensen's alpha is zero), the excess return of a portfolio is attributable to factor-risk premiums. The model can be estimated as follows:

$$Excess_{i,t} = \alpha + \beta_1 * MRP_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \varepsilon_{i,t} \quad (5)$$

where EXCESS is the excess return on portfolio, computed by subtracting the risk-free rate from the return on portfolio. The risk-free rate is measured as the 10-year government bond yield. MRP is the monthly market risk premium, measured by subtracting the risk-free rate from the market return. SMB is a size factor, measured as the difference between the returns on a portfolio of small cap stocks and on a portfolio of large cap stocks. HML is a value factor, measured as the difference between the returns on a portfolio of high book-to-market stocks and on a portfolio of low book-to-market stocks. MOM is a momentum factor, measured as the difference between the returns on a portfolio of winner stocks and on a portfolio of loser stocks (Please see the details of MRP, SMB and MOM construction in Appendix B.). The 4-factor model will generate Jensen's alpha while controlling for the covariance of portfolio returns with market return, size, B/M, and momentum factors.

3.2.2. Cross-sectional regression of stock returns

We examine the relation between the efficiency change and the cross-section of stock returns using the cross-sectional regression analysis of monthly returns on individual stocks. The augmented Fama-MacBeth (1973) model is estimated as follows:

$$R_{i,t+1} = \alpha + \beta_1 * Change_{i,t} + \beta_2 * Size_{i,t} + \beta_3 * B/M + \beta_4 * Turnover_{i,t} + \beta_5 * HHI_{i,t} + \varepsilon_{i,t} \quad (6)$$

where R is the monthly return on an individual stock in year t+1. Change is the level change in efficiency, CH, or percentage change in efficiency, %CH. SIZE is the natural logarithm of market capitalization, measured at December of year t. B/M is the natural logarithm of book value to market value, measured at the fiscal year end of year t. Similar to Fama and French (1992), we use SIZE and B/M to capture firm size effect and value effect, respectively.

Prior research found that liquidity plays a role in explaining the stock returns, even after controlling for size, book-to-market and beta in the US market (see Amihud and Mendelson, 1986; Chordia, Subrahmanyam and Anshuman, 2001) and in the Australian market (see Chan and Faff, 2003). Thus, we expect that market liquidity is one explanatory variable in our model. We use TURNOVER, calculated as the ratio of trading volume to shares outstanding over a year, as a proxy for market liquidity and expect it to be negatively associated with return as the higher liquidity, the lower ask-bid gap, the lower return and vice versa.

With respect to product market, in highly concentrated or regulated industries such as telecommunication and utilities industries, barriers to entry are high; thus, firms are likely to be insulated from distress risk, suggesting that the risk of poor operating decisions leading to distress is much lower (Hou and Robinson, 2006). This situation implies that firms operating in a highly concentrated industry would have lower risk than firms operating in a highly competitive industry, and hence, they would have lower return. On the other hand, firms operating in a monopolistic or oligopolistic market tend to have higher profitability and would thus have higher stock returns. Therefore, the expected sign of industry concentration on future stock returns is ambiguous. Following Hou and Robinson (2006), we use the Herfindahl index (HHI) as a proxy for industry concentration. An industry's HHI is computed by first calculating the sum of squared sales-based market shares of all firms in that industry during a given year and then averaging it over the past 3 years.

4. DATA AND DESCRIPTIVE STATISTICS

Our sample consists of 14,857 firm-year observations or 137,174 firm-month observations of listed companies across nine industry sectors in the ASX from January 1990 to October 2012. Consistent with prior studies, we also exclude firms in the financial industry[4] (e.g., banks, financial services, insurance) and firms with a negative book value of equity. The sample covers most firms in the ASX200 and the majority of the All Ordinary index composite over 22 years. The information on firms such as total assets, debts, sales, capital expenditure, stock price, daily trading volume and share outstanding is sourced from COMPUSTAT Global, while analyst forecasts are from I/B/E/S. The market index is obtained from DATASTREAM, and the risk-free rate is measured as the 10-year government bond yield sourced from the Reserve Bank of Australia[5]. Firms were classified into nine industries based on Standard and Poor's Global Industrial Classification Standard (GICS) sectors: energy (10), materials or mining (15), industrials (20), consumer discretionary (25), consumer staples (30), health care (35), information technology (45), telecommunication (50), and utilities (55)[6]. Chan, Lakonishok and Swaminathan (2007) argue that the use of GICS codes is an effective mean of characterizing industry, citing widespread use of the GICS code by investment portfolio managers and analysts (Docherty, Chan and Easton, 2011). All of our analyses use data available at time t to forecast stock performance at time t + 1, so there is no look-ahead bias induced by our statistical procedures.

[4] Financial firms often have high leverage, which does not necessarily mean that those firms are in financial distress, as it does with non-financial firms.

[5] Some prior studies on the Australian market, such as Chai, Faff and Gharghori (2013) and Braisford, Gaunt and O'Brien (2012), used the monthly return on the 13-week Treasury note as a proxy for the risk-free rate. However, these data have not been available for the Reserve Bank of Australia since 2006.

[6] The number within parentheses is the code for each industry sector.

Table 1. Descriptive statistics of variables in the frontier model and estimated efficiency score

Panel A of Table 1 presents descriptive statistics for the frontier model on the full sample and by industry. The average (median) firm has a Tobin's Q of 3.15 (1.65) and gross sales of $489.48 million ($10.75 million)[7]. The median firm report has a R&D/PPE of 0%, a CAPEX/PPE of 22% and an operating margin of 4%. On average, the leverage of the Australian firms is low, with an average leverage of just 8%, and analysts cover approximately one-third of firms in the market.

Panel A: Descriptive statistics of variables in the frontier model													
	Full sample				*Median by industry*								
	Obvs	*Mean*	*Std*	*Median*	*Energy*	*Materials*	*Industrials*	*Consumer discretionary*	*Consumer staples*	*Health care*	*Information technology*	*Telecom munication*	*Utilities*
Tobin's Q	14,857	3.15	4.36	1.65	2.10	1.92	1.24	1.43	1.27	2.40	1.58	1.67	1.39
Market value of equity ($M)	14,857	1,143.12	8,174.85	47.55	37.38	29.46	116.37	113.43	222.44	40.47	28.37	51.56	125.24
Sales ($M)	14,857	489.48	2,580.27	10.75	0.98	0.36	150.49	103.17	237.66	3.01	16.32	23.65	24.27
R&D/PPE	14,608	0.70	3.71	0.00	0	0	0	0	0	0.40	0	0	0
CAPEX/PPE	14,608	0.54	1.63	0.22	0.26	0.23	0.20	0.20	0.13	0.26	0.36	0.30	0.13
INC/Sales	13,105	-3.48	10.22	0.04	-0.67	-0.90	0.08	0.10	0.07	-0.69	0.03	0.05	0.20
PPE/Sales	13,127	5.49	13.96	0.41	2.69	1.71	0.18	0.15	0.33	0.22	0.06	0.21	3.03
LEV	14,857	0.08	0.14	0.00	0	0	0.08	0.06	0.12	0	0.00	0.01	0.08
FOLL	14,857	0.29	0.46	0.00	0	0	0	0	0	0	0	0	0
Panel B: Estimated efficiency score and its change in the period 1990-2011													
	Full sample				*Median by industry*								
	Obvs	*Mean*	*Std*	*Median*	*Energy*	*Materials*	*Industrials*	*Consumer discretionary*	*Consumer staples*	*Health care*	*Information technology*	*Telecom munication*	*Utilities*
EFFICIENCY	11,906	0.615	0.180	0.614	0.675	0.649	0.550	0.586	0.557	0.699	0.606	0.615	0.578
CH	10,098	-0.003	0.145	0.000	0.000	0.000	0.002	0.002	0.005	-0.006	-0.008	-0.012	0.010
%CH	10,098	0.031	0.294	0.000	0.000	0.000	0.004	0.004	0.007	-0.008	-0.014	-0.015	0.017

Tobin's Q is defined as the ratio of market value of equity plus book value of total debts to book value of total assets. The market value of equity equals to the product of price of stock at December of year t and share outstanding (in $million). Total assets and gross sales are values at the end of the fiscal year t, in $million. R&D/PPE is the ratio of R&D expenditure to net of property, plant and equipment. CAPEX/PPE is the ratio of capital expenditure to net of property, plant and equipment. INC/Sales is the ratio of operating income before depreciations and amortizations to gross sales. PPE/Sales is the ratio of net of property, plant and equipment to gross sales. LEV is the ratio f book value of long-term debts to sum of book value of long-term debt and market value of equity. FOLL is analyst following, takes value of unity if the firm is followed by analyst(s) and zero otherwise. EFFICIENCY is estimated efficiency score, measured as Q/Q. CH is level change in efficiency, computed as difference between efficiency score of year t and that of year t-1. %CH is percentage change in efficiency, computed as level change in efficiency divided by efficiency score of year t-1. All variables are winsorized at the 1% and 99% levels.*

[7] In this study, $ denotes Australian dollar AUD

5. EMPIRICAL RESULTS

5.1. Efficiency of Australian Firms and Industries

Panel B of Table 1 exhibits the estimated efficiency score of firms and its change from 1990-2011 in nine industries. The average firm has an estimated efficiency of 61.5%, implying an inefficiency of 38.5%, which is shortfall from the frontier line. Compared to an inefficiency of 16% for industrial firms reported by Habib and Ljungqvist (2005) and 30% reported by Nguyen and Swanson (2009), Australian companies during the period 1990-2011 tend to operate less efficiently than companies in the US. On average, health care and energy industries tend to operate above the average level of the broad market, whereas industrials, consumer discretionary, consumer staples, telecommunication and utilities tend to operate under it. Overall, in terms of level change, firm efficiency has remained almost unchanged. However, in terms of percentage change, firm efficiency tends to increase as the average firm has improved 3% per annum during the sample period.

Table 2. Mean parameter sensitivities from the frontier model

	Expected sign	*Mean of coefficient*	*t-value*
Ln(sales)	-	-0.20***	-5.46
R&D/PPE	+	0.31	1.66
CAPEX/PPE	+	0.18**	2.56
INC/Sales	+	-0.05	-1.61
PPE/Sales	+/-	0.004	0.24
LEV	+/-	-4.34***	-12.44
FOLL	+	0.46***	4.64
Constant		6.01***	7.93

*Note: This table reports the average of parameter sensitivities for stochastic frontier analysis for equation (1) using the sample of 14,857 firm-observations of listed companies in the Australian Securities Exchange (ASX) from January 1990 to October 2012. Dependent variable is Tobin's Q, measured as the ratio of the market value of equity plus book value of total debts to book value of total assets. The market value of equity equals to the product of price of stock at December of year t and share outstanding (in $million). Ln(sales) is the natural logarithm of gross sales. Book value of total assets, book value of total debts and gross sales are values at the end of financial year (in $million). R&D/PPE is the ratio of R&D expenditure to net of property, plant and equipment. CAPEX/PPE is the ratio of capital expenditure to net of property, plant and equipment. INC/Sales is the ratio of operating income before depreciations and amortizations to gross sales. PPE/Sales is the ratio of net of property, plant and equipment to gross sales. LEV is the ratio of book value long-term debts to sum of book value of long-term debt and market value of equity. FOLL is analyst following, takes value of unity if firm is followed by analyst(s) and zero otherwise. All ratios are winsorized at the 1% and 99% levels. The frontier model using SFA regresses with truncated-normal, running annually then following Fama and MacBeth (1973) we calculate the mean of time-series coefficients and their t-statistics by dividing mean by time-series standard deviation. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.*

At the end of each year, t, from January 1990 to December 2011, we estimate equation (1) using the stochastic frontier approach. Table 2 reports the mean parameter sensitivities from the frontier regression results. Following Fama and MacBeth (1973), we calculate the mean of time-series coefficients and their t-statistics based on 22 annual observations. The results are in line with the finding in Habib and Ljungqvist (2005). For instance, the average coefficient of ln(sales) is -0.20, which is close to the value of -0.31 reported in Habib and Ljungqvist (2005), suggesting that the average Q will fall as firms grow larger. The variables that proxy for soft-spending (R&D/PPE) and operating margin INC/sales are insignificant. Capital intensity or hard-spending (CAPEX/PPE), which proxies for growth opportunities, is positively related to Tobin's Q. Leverage (LEV) has a negative impact on firm value, whereas analyst following helps improve it.

Table 3. The large firms with the lowest percentage change in efficiency (%CH) in 2011

#	*Company*	*Industry*	*Market Capitalization ($M)*	*%CH*	*Return*
1	Billabong Int'l Ltd.	Consumer discretionary	675	-42.30%	-71.66%
2	Linc Energy Ltd.	Energy	587	-41.22%	-60.88%
3	Bathurst Resources Ltd	Materials	515	-41.01%	-40.19%
4	Arrium Ltd	Materials	1,564	-39.05%	-8.91%
5	Independence Group NL	Materials	1,088	-38.39%	-2.27%
6	Paladin Energy Ltd	Energy	1,309	-35.76%	-24.81%
7	Bluescope Steel Ltd	Materials	2,032	-33.27%	0.21%
8	Jetset Travelworld Ltd	Consumer discretionary	452	-32.64%	-47.00%
9	Energy Resources of Australia	Energy	2,892	-31.61%	3.20%
10	Mount Gibson Iron Ltd	Materials	1,246	-30.57%	-40.55%

Note: This table shows stock returns on the large firms (the top 200 firms in terms of market capitalization at the end of 2011) with the lowest percentage change in efficiency (%CH). Return is the compouded return from January 2012-October 2012.

Table 3 shows 10 large firms (in the top 200 in terms of market capitalization at the end of 2011) with the lowest percentage change in firm efficiency (%CH) in 2011. Intuitively, there is a positive relation between the change in firm efficiency in 2011 and subsequent stock returns in 2012; the greater the decrease in efficiency, the more significant is the plunge in stock price in the following year. Take Billabong Int'l Ltd, a retail company, for example. The company had extended[8] its business by investing and opening many shops in foreign countries but failed to compete with domestic shops

[8] Billabong Intl's acquisitions in 2010-2011 were $368 million, approximately 4.5 times higher than the $82 million in 2009-2010 (see the company's financial report, ended 30 June 2011).

and online stores in those markets. Consequently, many shops were closed, earnings dropped and the company's estimated efficiency fell from 60% in 2010 to just 34.5% in 2011. As a result, Billabong's price had declined considerably, losing almost 72% of its value from January 2012 to October 2012.

Table 4. Descriptive statistics of variables in the Fama-MacBeth model and correlation table

Panel A: Descriptive statistics of variables using in the Fama-MacBeth model						
	Obvs	*Mean*	*Std*	*Median*	*Min*	*Max*
R	137,174	-1.71%	17.46%	-1.28%	-61.68%	61.55%
CH	10,098	-0.003	0.145	0	-0.445	0.443
%CH	10,098	0.031	0.294	0	-0.603	1.392
SIZE	11,906	18.25	2.13	17.97	14.2	23.81
B/M	11,906	-0.87	0.95	-0.82	-3.65	1.35
TURNOVER	11,906	0.49	0.54	0.32	0	3.16
HHI	11,704	0.15	0.13	0.12	0.03	1
Panel B: Pearson cross-correlation coefficients table.						
	CH	*%CH*	*SIZE*	*B/M*	*TURNOVER*	*HHI*
CH						
%CH	0.930***					
SIZE	0.111***	0.033***				
B/M	-0.088***	-0.035***	-0.313***			
TUNROVER	0.064***	0.069***	0.205***	-0.145***		
HHI	-0.005	0.012	0.016*	-0.008	0.068***	

*R is monthly return on individual stock, calculated as the compounded daily return. Efficiency is estimated efficiency score. CH is change in efficiency score, computed as efficiency score of year t minus that of year t-1. %CH is percentage change in efficiency, computed as level change in efficiency divided by efficiency score of year t-1. SIZE is the natural logarithm of market value of equity, measured in December of year t. B/M is the natural logarithm of the ratio of book value to market value of equity, measured at the fiscal year end of year t. TUNROVER is calculated as the ratio of daily trading volume to shares outstanding over year t. An industry's Herfindahl index (HHI) is measured by first calculating the sum of squared sales-based market shares of all firms in that industry in a given year and then averaging over the past 3 years. Our sample of Australia is from COMPUSTAT Global in the period from Jan 1990 to Oct 2012. MRP is monthly risk premium, calculated as the market return less the risk-free rate. The risk-free rate is proxied by the 10-year government bond yield, sourced from the Reserve Bank of Australia. ***, **, * indicates significance at 1%, 5%, and 10% levels, respectively, for the correlation coefficients.*

Panel A of Table 4 shows the descriptive statistics of the full sample. Monthly market return is the value-weighted return on the broad market portfolio, sourced from DATASTREAM. The risk-free rate (Rf) is proxied by the 10-year government bond yield, sourced from the Reserve Bank of Australia. Monthly return (R) on individual stock is the compounded daily return within the month, sourced from COMPUSTAT Global. Return for the average firm (median) is -1.71% (-1.28%) per month. Those negative numbers are possibly attributable to the adverse effect of several financial crises that happened during the sample period such as the dot-com bubble crisis in the early 2000s and the global financial crisis (GFC) in 2008. TURNOVER is calculated as the ratio of the daily trading volume to shares outstanding over a year, and the average firm has a value of 49% per annum. An industry's Herfindahl index (HHI) is used to proxy for industry concentration; the higher the HHI, the more monopolistic is the market, whereas the lower the HHI, the more competition exists in the product market. An industry's HHI is computed by first calculating the sum of squared sales-based market shares of all firms in that industry during a given year and then averaging that value over the past 3 years. This approach is to ensure that the Herfindahl measure is not unduly influenced by potential data errors (Hou and Robinson, 2006).

Panel B of Table 4 shows correlation coefficients between our variables. There is a high correlation between CH and %CH (0.93), but the other correlation coefficients are quite low, implying that the multicollinearity is not a significant issue in our regressions.

5.2. Returns and change in the efficiency-sorted portfolio

Table 5 reports the mean returns on CH-sorted and %CH-sorted portfolios. Panel A presents the performance of portfolios during the period from January 1990 to October 2012, whereas Panels B and C present the results for the sub-period of the 1990s and 2000s, respectively. They exhibit the same pattern, as returns on portfolios tend to increase moving from the Low portfolio to the High portfolio. The statistics on the spreads show that the mean of return on the equally-weighted (value-weighted mean) spread CH-sorted portfolio over the full sample is 0.9% (0.6%) per month and statistically significant. This result implies that the High CH-sorted portfolio outperforms the Low CH-sorted portfolio by approximately 11% and 7%, respectively, on a compounded annual basis in terms of equally- and value-weighted returns. Notably, as observed in Panels B and C, most mean returns on portfolios during the 2000s tend to be lower than those during the 1990s. However, the spread of mean returns between the High and Low portfolios over the two sub-periods are similar to that in the full sample period.

Table 5. Mean monthly returns on CH-sorted and %CH-sorted portfolios

	CH -sorted portfolio		*% CH -sorted portfolio*	
Portfolio	***Equally-weighted***	***Value-weighted***	***Equally-weighted***	***Value-weighted***
Panel A: Full sample, Jan 1990-Oct 2012				
Low	-1.54%	-0.38%	-1.49%	-0.40%
Middle	-0.54%	0.35%	-0.58%	0.34%
High	-0.59%	0.27%	-0.60%	0.24%
Spread (High-Low)	0.9%***	0.6%***	0.8%***	0.6%***
Panel B: Subsample, Jan 1990- Dec 1999				
Low	-0.47%	-0.41%	-0.43%	-0.35%
Middle	0.13%	0.43%	0.13%	0.40%
High	0.46%	0.40%	0.42%	0.41%
Spread (High-Low)	0.9%***	0.8%**	0.8%**	0.7%**
Panel C: Subsample, Jan 2000-Oct 2012				
Low	-2.33%	-0.41%	-2.25%	-0.42%
Middle	-1.02%	0.29%	-1.12%	0.26%
High	-1.35%	0.24%	-1.33%	0.18%
Spread (High-Low)	1%***	0.6%*	0.9%***	0.6%*

*Note: This table displays equally and value-weighted monthly return on CH-sorted portfolios and %CH-sorted portfolios. I December of each year t, we rank all the stocks in the sample by efficiency change in ascending order. We then assign the sample int tertile portfolios. The first portfolio is Low that consists of firms with low improvement in efficiency, the second is Middle and the la: portfolio is High that consists of firms with high improvement in efficiency. All portfolios are held in 1 year from January to Decembe of year t+1 and are rebalanced at the end of each year. The SPREAD portfolio is a zero-cost portfolio that has a long position in th High portfolio and short position in the Low portfolio. The return series for the SPREAD portfolio is the difference between the Hig portfolio return and the Low portfolio return. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.*

To obtain more insight about the behavior of the High and Low portfolios, we draw graphs for the annual performance of the equally- and value-weighted CH-sorted portfolios in Figs. 1a and 1b. This method is repeated for the %CH-sorted portfolios, and we have Figs. 2a and 2b. As observed from the four figures, the outperformance of the High portfolio over the Low portfolio is not time period-specific but is present over most years in the sample period.

Figure 1a. Performance of the High vs Low equally-weighted CH-sorted portfolio

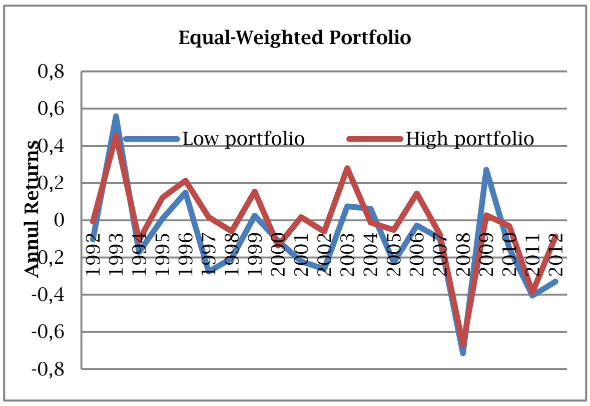


Figure 1b. Performance of the High vs Low value-weighted CH-sorted portfolio

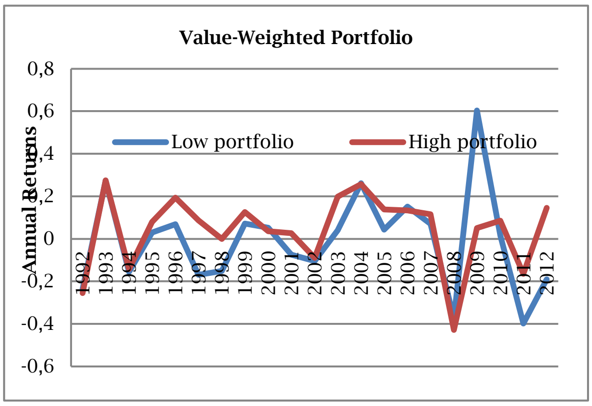


Figure 2a. Performance of the High vs Low equally-weighted %CH-sorted portfolio

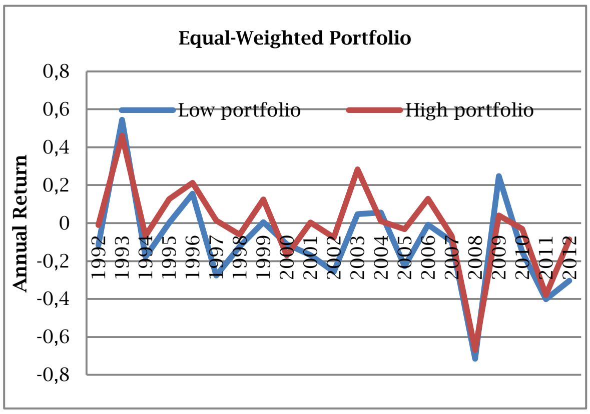
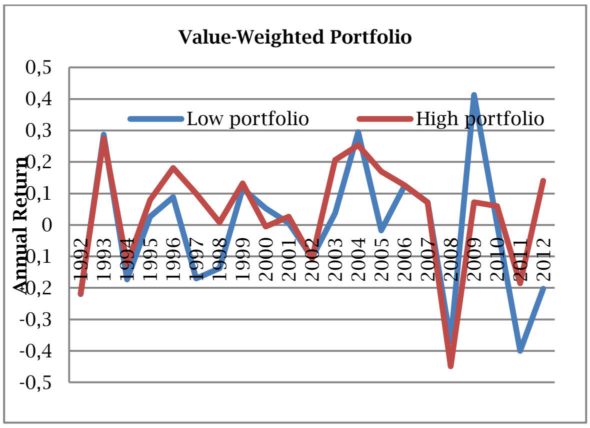


Figure 2b. Performance of the High vs Low value-weighted %CH-sorted portfolio



5.3. Effect of Efficiency Improvement on Stock Returns

5.3.1. The Carhart 4-factor models

To investigate the effect of efficiency change on returns over time, we will run the Carhart 4-factor model on the excess portfolio returns. In this model, MRP proxies for portfolio systematic risk, SMB proxies for firm size effect, HML proxies for book-to-market or value effect and MOM proxies for momentum effect. If Jensen's alpha is positive and significant, after adjusting for other risk-loading factors (i.e., beta, size, value and momentum effects), then the abnormal returns may be attributable to the efficiency change.

We follow Fama and French (1993) to calculate SMB and HML factors and follow Carhart (1997) to calculate the MOM factor during the period from January 1990 to October 2012. The mean magnitude of small-minus-big, SMB, is -2.08% pm. However, Brailsford, Gaunt and O'Brien (2012) report a mean SMB of -0.22% pm during the period 1982-2006[9]. The mean of HML is 1.17% pm, consistent with the finding in Halliwell, Heaney and Sawicki (1999), who document a premium of approximately 1.2% pm during 1981-1991, and with Gharghori, Chan and Faff (2006), who report a premium of 1.18% pm during 1990-2003. The mean of MOM is 14.97% pm, similar to the finding in O'Brien, Brailsford and Gaunt (2010)[10].

The regression results on CH- and %CH-sorted portfolios are displayed in Panel A and Panel B of Table 6, respectively. The coefficient values of the four different factors provide us with useful information regarding the different portfolios. In both Panels A and B, the parameter MRP is positive and significant for all portfolios, implying that there is an important role of systematic risk in explaining the variation of returns on portfolios. Furthermore, we observe that the market betas are highest for the Low portfolio in most cases, indicating that the Low portfolio tends to have higher levels of market risk than the High portfolio.

Turning to the SMB factor, it is worth noting that the magnitude of the SMB slope coefficient is the largest for the Low portfolio compared to other portfolios. This result indicates that there is a concentration of small-cap stocks in the low change in efficiency portfolio. Additionally, the Low portfolio seems to hold value stocks, as the slope coefficient of the HML factor is the highest. Taken together, the Low portfolio tends to consist of small-cap and value stocks. This finding is in line with Fama and French (1993), as smaller firms are more likely to be financially distressed. Financially distressed firms are more apt to suffer from inefficiency, as without access to external capital, firms may be forced to forgo investments with good growth opportunities, thus, firm value is not maximized (Chung et al., 2012). The loading on MOM is almost insignificant, suggesting that the momentum factor has limited power to explain the variation in stock returns over the sample period. This finding is similar to Kassimatis (2008), who finds that the momentum factor is statistically significant in explaining variation in returns for only 3 of 25 portfolios in his study.

Compared with other portfolios, Jensen's alpha on the equally- and value-weighted Low CH-sorted (%CH-sorted) portfolio is the lowest at -1.1% and -2.5% (-1.2% and 2.5%) per month, respectively, and significant in most cases. This result indicates that the Low portfolio tends to be overvalued. Taking the finding above that the Low portfolio is likely to consist of small-cap and value stocks, we can conclude that misevaluation is common among small-cap and value firms with a large decrease in firm efficiency. Jensen's alpha is 1.9% and 2.0% (1.9% and 2.1%) per month and significant at the 5% level for the equally- and value-weighted CH-sorted (%CH-sorted) spread portfolio, respectively. Notably, the magnitude of Jensen's alpha for the High portfolio is smaller than for the Low portfolio, suggesting that the abnormal return from the strategy of buying the High portfolio and short selling the Low portfolio is mainly driven by short positions.

We observe similar results to the 4-factor model on %CH-sorted portfolios in Panel B of Table 6. The Low portfolio also tends to have higher systematic risk, concentrate small-cap and value stocks and underperform the High portfolio. In sum, the results of our performance regressions show that efficiency change has a clear impact on subsequent stock price performance. This finding is present in both CH-sorted and %CH-sorted portfolios. Hence, these results are not model specific. The presence of an abnormal return after controlling for known risk factors (i.e., systematic risk, size effect, value effect and momentum effect) therefore would be attributable to the efficiency change.

5.3.2. The Fama-MacBeth (1973) model

The performance of the regressions above shows that a change in firm efficiency plays a role in explaining stock price performance over time. In this section, we assess whether firm efficiency change also plays a role in explaining the cross-section of stock returns.

Table 7 exhibits the results of the Fama-MacBeth (1973) regression analysis of the cross-section of stock returns on firm efficiency changes and other controlling variables for the full sample and by industry. Panel A exhibits the results of the regressions of monthly return on level change CH, whereas Panel B presents the results for percentage change %CH. The parameters estimated are the average of time-series coefficients and their standard deviations. The average slopes provide the standard Fama-MacBeth (1973) test for determining which explanatory variables on average have non-zero expected premiums (Fama and French, 1992) during the period from January 1990 to October 2012.

[9] There is one possible explanation for a negative number of the mean of SMB, which is that our sample period covers several financial crises such as the dot-com bubble that occurred in the early 2000s and the GFC in 2008. During those hard times, the returns for many firms, particularly small firms, declined significantly; as a result, the mean of SMB during the period 1990-2012 may be lower than that during other periods.

[10] For instance, O'Brien et al. (2010) report that the mean of returns for the large-cap value winners is 48.02%, and for the large-cap value losers, it is -33.21%, suggesting that the difference between large-cap value winners and losers is 81.23% per semi-annum or 13.54% pm; the mean of returns on the mid-cap growth winners is 60.52%, and on the mid-cap growth losers, it is -41.62%, suggesting that the difference between mid-cap growth winners and losers is 102.12% per semi-annum or 17.02% pm during the period 1981-2005.

Table 6. The Carhart 4-factor model

	Equally-weighted return				*Value-weighted return*			
	Low	*Middle*	*High*	*Spread (High-Low)*	*Low*	*Middle*	*High*	*Spread (High-Low)*
				Panel A: CH-sorted portfolios				
Alpha	-0.011	-0.005	0.008	0.019**	-0.025***	0.001	-0.005	0.020**
	(0.007)	(0.005)	(0.006)	(0.008)	(0.008)	(0.005)	(0.007)	(0.009)
MRP	1.091***	0.951***	1.031***	-0.060	1.048***	1.058***	0.938***	-0.110*
	(0.045)	(0.034)	(0.042)	(0.053)	(0.050)	(0.032)	(0.043)	(0.058)
SMB	0.758***	0.484***	0.641***	-0.117**	0.138***	-0.067**	-0.047	-0.185***
	(0.042)	(0.032)	(0.040)	(0.051)	(0.047)	(0.031)	(0.041)	(0.055)
HML	0.381***	0.354***	0.255***	-0.126*	0.264***	0.057	0.016	-0.248***
	(0.064)	(0.048)	(0.060)	(0.076)	(0.071)	(0.046)	(0.062)	(0.082)
MOM	0.023	0.013	-0.055	-0.078	0.127**	-0.025	0.016	-0.111*
	(0.049)	(0.037)	(0.046)	(0.058)	(0.055)	(0.035)	(0.047)	(0.063)
Adj_Rsq	0.796	0.814	0.789	0.018	0.649	0.812	0.655	0.064
N	250	250	250	250	250	250	250	250
				Panel B: %CH-sorted portfolios				
Alpha	-0.012*	-0.004	0.007	0.019**	-0.025***	0.001	-0.004	0.021**
	(0.007)	(0.005)	(0.006)	(0.008)	(0.008)	(0.005)	(0.007)	(0.010)
MRP	1.086***	0.971***	1.014***	-0.072	1.105***	1.017***	0.992***	-0.113*
	(0.043)	(0.034)	(0.042)	(0.052)	(0.050)	(0.033)	(0.048)	(0.063)
SMB	0.752***	0.475***	0.656***	-0.096*	0.174***	-0.082***	-0.006	-0.179***
	(0.041)	(0.032)	(0.040)	(0.049)	(0.048)	(0.031)	(0.045)	(0.060)
HML	0.389***	0.332***	0.271***	-0.117	0.338***	0.038	0.056	-0.282***
	(0.062)	(0.048)	(0.060)	(0.074)	(0.072)	(0.047)	(0.068)	(0.090)
MOM	0.031	-0.003	-0.047	-0.079	0.126**	-0.032	0.010	-0.117*
	(0.047)	(0.037)	(0.046)	(0.057)	(0.055)	(0.036)	(0.052)	(0.069)
Adj_Rsq	0.805	0.818	0.783	0.016	0.672	0.796	0.633	0.056
N	250	250	250	250	250	250	250	250

Dependent variable is monthly excess return on portfolios. The model is estimated as follows:

$$\text{Excess}_{i,t} = \alpha + \beta_1 * \text{MRP}_t + \beta_2 * \text{SMB}_t + \beta_3 * \text{HML}_t + \beta_4 * \text{MOM}_t + \varepsilon_t$$

Where Excess is the monthly excess return on portfolio, computed by subtracting the risk free rate from the return on portfolio. The risk free rate is measured as the 10-year government bond yield. MRP is monthly market risk premium, measured by subtracting the risk free rate from the monthly value-weighted market return. SMB is the size factor, measured the difference between returns on a portfolio of stocks with small cap and on a portfolio of stocks with large cap. HML is the value factor, measured as the difference between returns on a portfolio of stocks with high book-to-market and on a portfolio of stocks with low book-to-market. MOM is the momentum factor, measured as the difference between returns on a portfolio of winner stocks and on a portfolio of loser stocks. Standard errors are in parentheses. ***, **, * indicates significance at 1%, 5%, and 10% levels, respectively.

The average slope coefficient on CH for the full sample is 3.4% and statistically significant at 1%, implying that improvement in firm efficiency can help explain the variation in the cross-section of stock returns after controlling for size effect, value effect, market liquidity and industry concentration. On average, a one standard deviation increase in efficiency change would lead to a 3.4% standard deviation increase in the cross-section of stock returns during the next year.

Interestingly, as observed in Panel A, the effect of efficiency change on stock returns varies across industries. Overall, a level change in efficiency (CH) helps explain the cross-section of stock returns in six out of nine industries including mining, industrials, consumer discretionary, consumer staples, health care and utilities. It is worth noting that the six mentioned industries are highly competitive[11]. With the average of HHI being 0.05, the consumer discretionary industry is the most competitive industry in the Australian market. Take retail companies, for example. Traditional retailers face keen competition from online stores and thus, they are forced to introduce an online shopping option to compete for survival.

Although the 0.37 average of the utilities industry's HHI is not as low as in highly competitive industries, the utilities industry is seen as a risky industry due to its characteristics and the risks it has faced. For instance, because electricity generators are long lived (usually in excess of 40 years) and have capital-intensive assets, they tend to bear the inflation risk inherent with long-lived assets (Investment Reference Group Report, 2011). Moreover, investment in the utilities sector is also posed to other risks such as policy risks (i.e., retail price regulation, commitment to long-term emissions reduction trajectories) and market risks (i.e., uncertainty of future fuel prices, currency fluctuation). In addition, one of the outcomes of pricing carbon[12] that is difficult to predict is the demand response by customers to the higher prices resulting from a carbon price (Investment Reference Group Report, 2011).

Habib and Ljungqvist (2005) and Nguyen and Swanson (2009), among others, have documented that inefficient firms are forced to improve their performance to compete and survive in a competitive market. Therefore, efficiency improvement is essential to survive in a competitive market, which in turn becomes an important factor in the asset pricing models.

Compared to CH, Panel B shows that %CH tends to have weaker explanatory power, as the change in efficiency effect remains in just two out of nine industries (i.e., the consumer discretionary and utilities industries). This result is consistent with our finding above that efficiency improvement is crucial for a firm in a highly competitive or risky market, which in turn becomes an important factor in the firm's market valuation.

[11] The HHI of the consumer discretionary, industrials, mining, health care, consumer staples and utilities industries are 0.05, 0.06, 0.15, 0.15, 0.19 and 0.37, respectively.

[12] A carbon tax came into effect on July 1, 2013.

Table 7. The Fama-MacBeth (1973) cross-sectional regression of monthly stock returns on efficiency change

		By industry								
	Full sample	***Energy***	***Materials***	***Industrials***	***Consumer discretionary***	***Consumer staples***	***Health care***	***Information technology***	***Telecom munication***	***Utilities***
Panel A: level change in efficiency (CH)										
CH	0.034***	-0.002	0.033***	0.032*	0.100***	0.050*	0.165*	-0.043	0.538	0.280**
	(0.154)	(0.513)	(0.224)	(0.272)	(0.334)	(0.417)	(1.368)	(3.478)	(5.651)	(1.507)
SIZE	0.005***	0.005***	0.005***	0.005***	0.004***	0.004***	0.008***	0.008***	0.005	0.013
	(0.010)	(0.020)	(0.014)	(0.014)	(0.019)	(0.018)	(0.035)	(0.040)	(0.169)	(0.193)
B/M	0.008***	0.007**	0.007***	0.008***	0.002	0.003	0.0006	0.011***	0.070	0.027
	(0.008)	(0.055)	(0.026)	(0.038)	(0.029)	(0.048)	(0.139)	(0.067)	(0.663)	(0.496)
TURNOVER	-0.014***	0.0008	-0.014***	-0.009***	-0.019***	-0.016***	-0.054***	0.004	-0.037**	-0.015
	(0.042)	(0.087)	(0.051)	(0.093)	(0.096)	(0.092)	(0.286)	(0.145)	(0.239)	(0.487)
HHI	-0.009*									
	(0.079)									
Constant	-0.092***	-0.086**	-0.096***	-0.086***	-0.062**	-0.078***	-0.162***	-0.148***	0.089	-0.244
	(0.217)	(0.418)	(0.291)	(0.270)	(0.381)	(0.340)	(0.816)	(0.891)	(5.618)	(3.878)
N	238	250	250	250	250	250	250	250	166	178
Panel B: percentage change in efficiency (%CH)										
%CH	0.012**	0.001	0.010	0.010	0.039***	0.023	0.027	-0.036	0.054	0.126***
	(0.077)	(0.223)	(0.120)	(0.137)	(0.175)	(0.227)	(0.649)	(2.342)	(2.635)	(0.575)
SIZE	0.005***	0.005***	0.005***	0.005***	0.003***	0.004***	0.006***	0.007***	0.016**	0.008
	(0.011)	(0.020)	(0.014)	(0.014)	(0.019)	(0.019)	(0.037)	(0.043)	(0.091)	(0.103)
B/M	0.007***	0.007**	0.006***	0.007***	0.002	0.002	0.005	0.010**	0.017	0.015
	(0.015)	(0.054)	(0.026)	(0.039)	(0.028)	(0.047)	(0.111)	(0.070)	(0.352)	(0.260)
TURNOVER	-0.014***	0.0002	-0.013***	-0.010*	-0.020***	-0.017***	-0.056***	0.004	-0.035*	-0.024
	(0.042)	(0.085)	(0.051)	(0.086)	(0.096)	(0.093)	(0.299)	(0.152)	(0.236)	(0.299)
HHI	-0.010**									
	(0.079)									
Constant	-0.095***	-0.088***	-0.097***	-0.089***	-0.066***	-0.081***	-0.123**	-0.147**	-0.320	-0.141
	(0.219)	(0.413)	(0.291)	(0.269)	(0.370)	(0.344)	(0.801)	(0.898)	(2.880)	(2.088)
N	238	250	250	250	250	250	250	250	166	178

This table reports monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns (R) in year t+1 on efficiency changes and other variables in year t, the model is estimated as follows:

$$R_{i,t+1} = \alpha + \beta_1 * Change_{i,t} + \beta_2 * SIZE_{i,t} + \beta_3 * B/M + \beta_4 * TURNOVER_{i,t} + \beta_5 * HHI_{i,t} + \varepsilon_{i,t}$$

*Where R is monthly return on individual stock in year t+1. Change is CH or %CH where CH is level change in efficiency year t compared to year t-1 and %CH is percentage change in efficiency year t compared to that of year t-1. SIZE is the natural logarithm of market value of equity, measured in December of year t. B/M is the natural logarithm of the ratio of book value to market value of equity, measured at the accounting balance date of year t. TURNOVER is calculated as the ratio of daily trading volume to shares outstanding over year t. An industry's HHI is measured by first calculating the sum of squared sales-based market shares of all firms in that industry in a given year and then averaging it over the past 3 years. R, TURNOVER and HHI are sourced from COMPUSTAT Global. Following Fama and MacBeth (1973) we calculate the average slope as the time-series average of the monthly regression slopes for January 1990 to December 2011. To avoid biased results caused by outliers, all variables are winsorized at the 1% and 99% levels. Standard deviations are in parentheses. ***, **, * indicates significance at 1%, 5%, and 10% levels, respectively.*

The slope coefficient on SIZE is significantly positive and quite stable across industries. This is not surprising, as prior studies of the Australian market report mixed results for the size effect. For instance, Docherty, Chan and Easton (2013) document that the size premium is nonlinear and driven by microcaps, whereas Faff (2001) finds evidence of large-firm indices outperforming small-firm indices. Liew and Vassarou (2000) have argued that small firms are riskier than large firms, making them a very risky investment in bad times because they have less chance of survival. Rational investors will hold small firms during good times, raising their prices, and will avoid them during bad times, pushing their returns down (Kassimatis, 2008). In addition, institutional investors tend to invest in larger firms and push up their stock prices (Gompers and Metrick, 2001). Taken together, with the dot-com bubble that occurred in the early 2000s and the GFC in 2008, returns on small firms would decline greatly during the 2000s. This might explain why large firms tended to outperform small firms in the Australian market during the 2000s.

Consistent with findings in prior studies (see Fama and French, 1992; Brailsford, Gaunt and O'Brien, 2012; Gharghori, Stryjkowski and Veeraraghavan, 2013; Docherty et al., 2013), we also find that book-to-market ratio is positively associated with stock return, implying that the required rate of return will be higher to compensate for firms in financial distress. The slope coefficient on share turnover is negative and significant in most industries, suggesting that investors require higher returns to compensate for illiquidity risk. The loading on HHI of -0.009 (-0.01) in Panel A (Panel B) is significant, revealing that the more competitive a market is in which firms operate, the higher the expected returns on firms' stocks.

A possible explanation for the correlation between efficiency change and subsequent stock return is that mispricing tends to be common among small-value firms, which have a large drop in firm efficiency. If a decrease in firm efficiency would cause additional agency costs in a subsequent year and if investors underestimate these additional costs, then a firm's performance should be worse than expected (Gompers et al., 2003). This situation implies that the firm's value at the beginning of the period would be too high or that the firm is overvalued. The stock price would move back to its intrinsic value, which is lower than the initial expectation. As a result, the subsequent stock return would be lower than expected. Alternatively, firms with a greater change in firm efficiency would better utilize their resources and would thus be more profitable and have higher subsequent stock returns.

However, due to the endogeneity issue for the firm efficiency change variable, agency cost proxies and firm performance proxies, further study is needed to tease out the exact cause of the relation we document.

5.4. Robustness test

According to the tax-loss selling hypothesis, because investors can use their investment losses to offset gains to reduce their tax, stocks that have declined in value tend to be sold at the end of the financial year. Consequently, as the supply of such stocks drops in the following month, their prices would increase and they would tend to perform well. Because Australia has a July-June taxation cycle, we also expect that a seasonality effect exists in July. Prior research also finds that the January effect exists in the Australian market, as there is a high integration between the Australian market and the US market (see Brown, Keim, Kleidon and Marsh, 1983; Brailsford and Easton, 1993). To avoid the effect brought by seasonality, we remove January and July firm observations.

The Carhart 4-factor model and the cross-sectional Fama-MacBeth model are re-run without January or July observations. We find that the results without those months' observations are consistent with the full sample results[13], implying that the efficiency change effect remains regardless of the seasonality effect.

We also run the CAPM, Fama-French 3-factor models for the full sample and the sub-sample without January or July observations and find that the unreported results are in line with those from the Carhart 4-factor model with the same conclusion.

6. CONCLUSION

This paper investigates whether investors in the Australian context value firm efficiency improvement at all. In particular, it examines how contemporaneous change in firm efficiency can be used to predict future stock performance in non-financial industries in Australia.

We employ a stochastic frontier analysis to estimate firm efficiency for a large panel of Australian listed companies from January 1990 to October 2012 and then examine the relation between the firm efficiency change and subsequent stock returns. Firm efficiency is estimated by comparing a benchmark Tobin's Q of a hypothetical value-maximizing firm to the firm's actual Tobin's Q. The change in efficiency is measured as level change and percentage change in firm efficiency in the current year compared to that in the previous year.

We find that an equally-weighted (value-weighted) portfolio of stocks with a high change in efficiency outperforms an equally-weighted (value-weighted) portfolio of stocks with a low change in efficiency by an average of 11% (7%) per annum. In cross-sectional analysis, efficiency improvement helps explain the variation in the cross-section of stock returns, even after controlling for known risk factors such as size, book-to-market, market liquidity and industry concentration. Furthermore, the cross-sectional regression results by industry reveal that firm efficiency improvement helps explain the cross-section of stock returns in six out of nine industries: materials, industrials, consumer discretionary, consumer staples, health care and utilities. It is worth noting that these industries are highly competitive. Therefore, this result is consistent with the notion that efficiency improvement is essential to compete and survive in a competitive market, which in turn becomes an important factor in the asset pricing model.

[13] Results for the Carhart 4-factor and cross-sectional Fama-MacBeth models without January or July observations have not been reported for the sake of brevity but are available from the authors on request.

Our findings confirm the importance of improvements in firm efficiency; the higher the improvement in efficiency is, the higher the subsequent stock returns. The results indicate the alignment between firm efficiency improvement and maximization of shareholders' wealth. Thus, our findings indicate that investors in the Australian stock market value improvement in firm efficiency. This finding therefore provides further impetus for the drive within Australia to improve the productivity and efficiency of the country, particularly in its industries and firms. It is comforting to know that the capital market also supports this, as it rewards firms that improve efficiency through higher stock returns. These findings also provide a signal to investors such as fund managers in their search for assets that can yield high returns. Finally, these results have implications for asset pricing theories: efficiency change, at least in the Australian context, is a factor that can explain changes in future returns.

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Appendix A: Variable definitions

Variables	*Definitions*
Frontier model	
Tobin's Q	Tobin's Q is defined as the ratio of market value of equity plus book value of total debts to book value of total assets
ln(sales)	The natural logarithm of gross sales
R&D/PPE	The ratio of research and development expenditures (R&D) to the stock of property, plant, and equipment (PPE); R&D is set to zero if missing
CAPEX/PPE	The ratio of capital expenditure to PPE
INC/Sales	Operating margin is measured as the ratio of operating income before depreciations and amortizations to gross sales
PPE/Sales	The ratio of PPE to gross sales
Lev	The ratio of book value of long-term debt to the sum of book value of long-term debt and market value of equity
Foll	Analyst following equals unity if the firm is followed by analyst(s) or 0 otherwise
Stock returns regressions	
R	Monthly return on individual stock in year t+1
Rf	Risk-free rate; proxied by the government 10-year bond yield in year t+1
Efficiency	Firm efficiency; the ratio of the firm's actual value to the hypothetically best-performing value of the firm as Q/Q*
CH	Level change in efficiency; the difference in efficiency between the current year and the previous year
%CH	Percentage change in efficiency; change in efficiency divided by the previous year's firm efficiency
SIZE	Natural logarithm of market value of equity; measured at December year t
B/M	Natural logarithm of ratio of book value to market value of firm equity at the accounting balance date of year t
Turnover	Calculated as ratio of daily trading volume to shares outstanding over year t
HHI	Industry concentration; calculated as the average of HHI over the past 3 years: $HHI = \sum_{i=1}^{I}(\frac{\text{Sales of firm i}}{\text{total industry sales}})^2$
Excessew	Excess equally-weighted monthly return on portfolio; calculated by subtracting the risk-free rate from the equally-weighted monthly return on the portfolio
Excessvw	Excess value-weighted monthly return on portfolio; calculated by subtracting the risk-free rate from the value-weighted monthly return on the portfolio
MRP	Market risk premium; calculated by subtracting the risk-free rate from the market return
SMB	Return on the mimicking size portfolio; measured as the difference between the returns on a portfolio with small cap and on a portfolio with large cap
HML	Return on the mimicking book-to-market portfolio; measured as the difference between the returns on a portfolio with high book-to-market and on a portfolio with low book-to-market
MOM	Return on the mimicking momentum portfolio; measured as the difference between the returns on a portfolio of winner and on a portfolio of loser

Appendix B: SMB, HML and MOM construction

For the SMB and HML factors, following Fama and French (1993), we form six portfolios from the intersections of two size and three book-to-market portfolios. At the end of December of year t-1, we first rank stocks according to their market capitalization, and the median market capitalization is used to split stocks into two groups—small and big. Similar to Braisford et al. (2012), the top 200 firms by market capitalization are ranked by their book-to-market ratios and separated based on the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high). These book-to-market breakpoints are recorded and used to assign all other firms outside the top 200 into the three book-to-market portfolios.

Monthly value-weighted returns on the six portfolios are calculated from January to December of each year. The portfolios are reformed at the end of each December. SMB (Small Minus Big) is the average return on the three small-size portfolios minus the average return on the three big-size portfolios. HML (High Minus Low) is the average return on the two high book-to-market portfolios minus the average return on the two low book-to-market portfolios.

Following Carhart (1997), we construct the momentum factor (MOM) as the equally-weighted average of firms with the highest 30% six-month returns, lagged one month, minus the equal-weight average of firms with the lowest 30% six-month returns, lagged one month. These momentum portfolios are rebalanced on a monthly basis..