Electricity Usage, Future Earnings, and Stock Prices

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Abstract: In this paper, we examine whether the change of electricity usage is informative about subsequent earnings changes. We anticipate that electricity usage is a leading indicator for future sales and increased electricity will lead to higher earnings. Using hand-collected data on electricity usage for Korean firms for the sample period of 2006- 2014, we find a positive association between changes in electricity usage and subsequent earnings after controlling for factors that may affect future profitability. We also report that changes in electricity usage predict future stock returns. A positive relation between electricity changes and future returns still holds even after controlling for the fundamental signals and various risk factors. A hedge portfolio strategy that buys the top quintile of electricity changes and sells the bottom quintile of electricity changes leads to an economically significant 4.80% annual abnormal return. In addition, we find evidence that the positive relation between changes in electricity and future returns is more salient for firms with high information asymmetry. Overall, the results suggest that firms' electricity usage is an important indicator for future profitability and investors do not fully incorporate the implications of electricity usage for future profitability.

1. Introduction

The purpose of this study is to examine whether electricity usage at the firm level is useful in predicting future earnings and stock returns. We expect that firms that increase electricity usage will generate higher earnings. In other words, electricity usage is a leading indicator that manifests future sales growth and thus companies that exhibit an increase in electricity usage are more likely to report higher earnings in the future.

The changes in the value-relevance of financial statements have increased research on leading indicators and non-financial disclosures. For example, prior research emphasizes the importance of nonfinancial metrics from customer, business process, and technology perspectives (Kaplan, 1983; Kaplan and Norton, 1992) in the performance and reward systems. In valuing firms, researchers have also provided evidence that non-financial measures are an important value driver (Myers, 1999; Trueman, et al, 2000; Francis et al. 2003; Rajgopal et al, 2003; Ittner et al. 2009). However, firms' disclosures on non-financial indicators are sparse and limited to certain industries (Amir and Lev, 1996) and mostly qualitative (for example, discussion on the firm's productivity and competitive advantages in MD &A). We are unaware of any research that examines the value-relevance of electricity usage. In this paper, we fill the void in the literature by collecting information on a quantitative non-financial indicator of future sales growth, namely electricity usage, and examine whether this leading indicator is informative about future earnings and stock prices.

Recently, Da, Huang, and Yun (2015) examine the stock market's response to U.S. industrial electricity usage and find that the industrial electricity usage growth rate is negatively related to future stock returns up to one year. In this study, we provide another examination of the value-relevance of electricity usage using a comprehensive firm-level dataset.

Korea offers a particularly unique setting that allows us to examine the effect of electricity usage on accounting profitability and stock prices at the firm level. Unlike the deregulated U.S. electricity industry, electricity customers in Korea are served by a regulated monopoly utility, KEPCO (Korea Electric Power Corporation). Currently, 6 power generation companies, independent power producers, and community energy systems produce electric power in Korea and KEPCO solely transports the electric power it purchased from the Korea Power Exchange through the transmission and distribution networks, and sells to end-use customers including firms. In other words, KEPCO, as a highly regulated monopolistic electricity transmitter has a tight control of the transmission networks and electricity service and as such, electricity usage data provided by KEPCO is a comprehensive representation of the entire electricity usage. This monopolistic position of KEPCO makes the firm-level electricity usage an even more reliable measure of a firm's future sales growth, because a firm has to abide by the KEPCO's terms and conditions no matter what the price or regulations are, due to lack of substitutable electricity providers. In other words, the electricity usage is unlikely to be influenced by external factors other than a firm's operating activity. We manually collect information on branch-level electricity usage provided by KEPCO and transform it at the firm-level and relate firm-level electricity usage to corporate profitability and stock prices. We believe that Korea-based evidence would shed important light on the relation between firm-level electricity information and operating and stock market performance measures.

We test our prediction about electricity usage with a large sample of Korean firms over the period of 2006-2014. In a univariate analysis, we find strong evidence that electricity changes predict future earnings changes. We continue to find that those firms with an increase in electricity usage tend to report higher earnings even after controlling for various signals, suggesting that firms with increased electricity usage are more likely to report higher earnings in the future. More importantly, we examine whether the market fully incorporates the information of changes in electricity usage for firm value and find a significant positive relation between changes in electricity usage and future returns. This positive relationship between changes in electricity usage and future returns continues to hold even after controlling for risk factors. A hedge portfolio that takes a long position in the highest quintile of electricity changes and takes a short position in the lowest quintile of electricity changes yields a 4.80% excess annual return. Furthermore, we examine the relation between changes in electricity usage and future returns conditioned on information asymmetry and find that the positive relation is primarily driven by firms with high information asymmetry.

To summarize, these results support the view that electricity usage is an important value driver and financial markets do not quickly incorporate information on electricity usages into stock prices.

We contribute to prior research in several ways. Extant research indicates that fundamental signals from financial statements are value-relevant and are useful in predicting future earnings (Ou and Penman, 1989; Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997; Piotroski, 2000; Piotroski and So, 2012). In our paper, we focus on the roles of electricity usage and show that electricity usage is incremental to signals in predicting future earnings. Thus, we extend the growing literature on non-financial indicators and leading indicators (for example, Deng, Lev, and Narin, 1999; Amir and Lev, 1996; Rajgopal et al, 2003; Ittner et al. 2009) by highlighting the importance of electricity usage, a leading non-financial indicator, for future performance. Second, our study is closely related to recent work by Da et al. (2015) reporting that the industrial electricity usage growth rate predicts future stock returns. We extend Da et al.

(2015) by showing that firm-level electricity usage predicts future returns. More broadly, our study adds to the literature on stock price anomalies (Sloan, 1996; Hirshleifer et al. 2013; Rapach and Zhou, 2013) by showing the mispricing of a leading indicator of a firm's real activities. Thus, our paper contributes to the literature by relating a firm's real economic activities and its performance in financial markets.

We believe that this finding is important to investors and analysts in making investment and valuation decisions.

The rest of this paper is organized as follows. In section 2, we develop our hypotheses with a review of the literature. We describe research design and data in section 3. We report results of our hypothesis in section 4. Section 5 provides the summary and conclusions.

2. Related Literature and Hypothesis Development

This paper extends prior research on non-financial leading indicators and stock price anomalies by introducing a non-financial leading indicator to predict future performance.

A stream of research examines the relation between fundamental signals and future performance. Ou and Penman (1989) suggest the Pr-measure using financial ratios from financial statements and predict the direction of future earnings changes. They also present a trading strategy based on the predictions. Holthausen and Larcker (1992) employ a model to forecast future stock returns. Lev and Thiagarajan (1993) adopt a regression framework to examine the value-relevance of twelve fundamental signals identified from analysts' research reports, such as inventory, capital expenditure, and gross margin. They find that these financial signals are closely related to contemporaneous returns.

Extending the findings in Lev and Thiagarajan (1993), Abarbanell and Bushee (1997) and Abarbanell and Bushee (1998) focus on nine variables out of Lev and Thiagarajan (1993) and explore whether these fundamental signals predict future earnings changes and stock prices. They show that these signals anticipate both future earnings changes and analyst revisions. They further find that the fundamental signals generate abnormal returns. Piotroski (2000) and Piotroski and So (2012) also underscore the importance of historical financial statements by showing that even within the portfolio of high book-to-market firms, financial statement information separates winners from losers. These findings suggest that the market underreacts to the value-relevant information embedded in financial statements.

While prior research suggests that the information contained in financial statements is value-relevant, prior studies also show that the explanatory power of accounting numbers has decreased over the last few decades (Francis and Schipper 1999; Collins et al. 1997). Relatedly, another stream of research indicates that non-GAAP leading indicators such as satisfaction measures (Ittner and Larcker 1998; Ittner et al. 2009), patent (Deng et al. 1999; Hirshleifer et al. 2013), market penetration (Amir and Lev 1996), order backlogs (Rajgopal et al. 2003), and eyeball measures in the internet industry (Trueman et al. 2000) are value-relevant and informative about future performance. These studies imply that non-financial measures can be leading indicators of financial performance.

In this study, we extend prior research on fundamental analysis and non-financial leading indicators by introducing a measure of a firm's real activities to predict future performance. We collect information on a firm's electricity usage to examine whether this measure is informative about future profitability and stock performance. While there is an abundance of research on fundamental signals, we are unaware of any research that relates firm-level electricity usage to future performance. Recently, Da et al. (2015) employ U.S. industrial electricity usage to predict stock returns and find that high industrial electricity usage predicts low stock returns in the future. However, they stop short of examining the impact of firm-level electricity usage and returns due to data availability. By utilizing a unique setting for Korean firms, we take further step and investigate whether firm-level electricity usage is informative about future performance from a fundamental analysis perspective. We expect that firms that increase in electricity usage are likely to increase their production levels in accordance with projected demand. Consequently, they will exhibit better operating performance than firms that do not do so. To the extent that electricity usage reflects production levels to match with varying demand, we expect to observe a positive relation between changes in electricity changes and future earnings changes. Our hypothesis follows, as stated in an alternative form:

H1. Changes in electricity usage are positively associated with future earnings changes.

Furthermore, we examine whether investors see through the implication of changes in electricity usage for future profitability, if any. In an efficient market, any systematic relation will be impounded efficiently into stock prices so we do not observe any relation between the changes in electricity usage and future stock prices. However, provided that investors fail to fully see through the implication of electricity usage and slowly respond to the information, there should be a significant positive relation between a firm's electricity usage growth and subsequent stock returns. Thus, where or not investors unravel this relation is an empirical question. We generate our second hypothesis, formulated in an alternative form as follows:

H2. Changes in electricity usage are positively associated with future returns.

3. Data and Research Design

Data

We report the sample selection procedure in Table 1. Our initial sample consists of 231,246 branch-month observations from year 2005 to 2014. [1] We delete branch-month observations if the number of monthly observations for a given year is less than 12, losing 8,154 branch-months. To mitigate the effect of the irregularities in the electricity usage when KEPCO first begins to provide electricity to a certain client firm, we also eliminate first six months of branch-month observations from the sample unless the electricity usage figure starts from January 2005, the very first month of our sample period. This leads our sample to amount to 218,004 branch-month observations. We aggregate the branch-month observations into 53,292 firm-months.[2] To obtain stock prices and accounting information used for analysis, we require that our sample firms have information on stock prices and accounting information on KISVALUE and FNDATAGUIDE (which is comparable to CRSP and Compustat, respectively), yielding 35,153 firm-month observations. To mitigate backfilling biases, we also require that a firm must be listed in the sample for 6 months before it is included in the data set (Fama and French 1993). Our final sample comprises 34,207 firm-month observations for the sample period of 2006-2014. In order to control for weather fluctuations in the analysis, we extract information on temperature from NCDSS(National Climate Data Service System).

[1] Since electricity usage figures that sporadically appear or disappear in the middle of our sample period are likely to yield extreme outliers, we calculate the standard deviation of electricity usage (ELECSTD) and delete branch-months if ELECSTD exceeds 1. ELECSTD is computed as the standard deviation of firm-level electricity usage divided by the average firm-level electricity usage, calculated at branch-level.

[2] We manually collected the names and stock codes of the KOSPI and KOSDAQ firms to ensure that the names of the firms in the electricity usage file are correctly matched with KISVALUE (comparable to CRSP) and FNDATAGUIDE (comparable to COMPUSTAT). In case there were more than two firms with the same name, we used the firm's location information and the name of the firm's representative to match each firm with an appropriate stock code.

Research Design

To test the association between change in electricity usage and future earnings, we follow prior research that has examined the indicators of future profitability growth (see, e.g., Abarbanell and Bushee 1997; Soliman 2008) and estimate the following OLS regression model:

$$\Delta ROA_{q+1} = \alpha + \beta_1 \Delta ELEC_t + \beta_2 SIZE_t + \beta_3 BTM_t + \beta_4 PASTRET_t + \beta_5 LEVERAGE_t + \beta_6 \Delta ROA_q + \beta_7 ROA_q + \beta_8 D\_LOSS_t + \varepsilon \qquad (1)$$

ΔROA_{q+1} is subsequent quarter's year over year changes in ROA, i.e., $ROA_{q+1} - ROA_{q-3}$. Throughout the analysis, subscript q refers to the quarter to which the month t belongs. $\Delta ELEC_t$ is the year over year changes in a firm's monthly electricity usage deflated by average total assets. The average total asset is calculated as the seasonally averaged total asset from the preceding quarter. $SIZE_t$ is the natural logarithm of (1 + a firm's market capitalization divided by 100,000). BTM_t is the natural logarithm of (1 + a firm's book value of equity to market value of equity). $PASTRET_t$ is the monthly compounded return of a firm for period [t-12, t-1], and $LEVERAGE_t$ is the natural logarithm of a firm's total asset deflated by book value of equity. ΔROA_q is the year-over-year change in ROA (i.e., $ROA_q - ROA_{q-4}$), where ROA_q is calculated as the net income of quarter q, divided by the beginning of the quarter total assets, multiplied by 100. D_LOSS_t is an indicator variable equal to one for firms reporting a loss in the quarter to which the month t belongs, and zero otherwise. Note that because information from financial statements is available only at the quarterly level, the most recent quarter was used for each month's measure.

As we expect a positive relation between electricity changes and future profitability changes, we expect a positive β_1 estimate.

To explore whether the market recognizes the implications of change in electricity for profitability, we next investigate whether changes in electricity usage predict future returns by estimating the regression model as follows:

$$RET_{t+1} = \alpha + \beta_1 \Delta ELEC_t + \beta_2 SIZE_t + \beta_3 BTM_t + \beta_4 PASTRET_t + \beta_5 LEVERAGE_t + \beta_6\, E/P_t + \varepsilon \qquad (2)$$

RET_{t+1} is a firm's one-month-ahead stock return, obtained from the KISVALUE database. E/P_t is a firm's net income over the end price of a firm's stock, divided by 1,000. All other variables are as previously defined, and can be found in the appendix.

If the market slowly (efficiently) incorporates the implication of the change of electricity usage for future profitability, we anticipate a positive (an insignificant) β_1.

4. Empirical Results

We report the descriptive statistics of the variables used for our analysis in Table 2. To be consistent with our regression analysis, we follow the Fama-Macbeth approach in calculating the descriptive statistics. Our key variable of interest is the change of electricity usage denoted as $\Delta ELEC_{t}$. To address seasonality in electricity usage, we define $\Delta ELEC_t$ as the year-over-year change of a firm's monthly electricity usage, normalized by average total assets. As can be seen from the table, the average firm's electricity growth is 0.077, with a substantial variation in monthly electricity usage. Mean and median values of monthly stock returns, denoted as RET_{t+1}, are 1.1% and 1.1% respectively. Returns are measured one month ahead of changes in electricity usage. One- quarter-ahead changes in ROA, denoted as ΔROA_{q+1} has a mean of -0.102.

We also consider a variety of control variables from prior literature that are potentially correlated with changes in future returns and profitability. The control variables for the return analysis include beta ($BETA_t$), size ($SIZE_t$), book to market (BTM_t), past returns ($PASTRET_t$), leverage ($LEVERAGE_t$) and earnings to price (E/P_t). All the variables are calculated as defined in the Appendix. The mean value for $BETA_t$, defined as the market beta calculated over previous 60 months, are 0.994. $SIZE_t$ variable reports the mean value of 1.517 and the median value of 1.440. The mean (median) values for BTM_t and $PASTRET_t$ are 0.818 (0.819) and 0.187 (0.112), respectively. These variables are included in our analysis to control for the value effect and the momentum effect. $LEVERAGE_t$ has mean and median values of 2.916 and 2.888 with a standard deviation of 0.276, and E/P_t, a firm's net income divided by stock price, has mean and median values of 0.070 and 0.379. ΔROA_q is negative on average, with a mean of -0.102. D_LOSS_t indicates that 25% of our sample firms incur losses.

Table 3 presents correlations among the key variables. As expected, the change of electricity usage is positively related to the change in one-quarter ahead profitability at the 1% level, implying that increased electricity usage is informative about an improvement in future profitability. We also find that the change of electricity usage is significantly and positively related to one-month ahead returns. These results provide initial evidence consistent with both H1 and H2.

The correlation coefficients among the control variables indicate that except for only a few pairs, correlations between most of the variables are statistically significant. However, the magnitudes of the correlations are not that large. For example, the largest correlation (in absolute terms) is between change in ROA and contemporaneous ROA, which is 0.5620. Most remaining correlations are at modest levels, implying that multicollinearity would not be a serious concern.

Nevertheless, we appropriately control for these control variables in a multivariate framework to establish a causal link between electricity usage and future performance.

Extending the positive and significant correlation coefficient between change in electricity usage reported in Table 3, in Figure 1, we report annualized hedge portfolio returns for each calendar year during our sample period. The hedge portfolio is constructed by ranking firms into deciles based on $\Delta ELEC_t$ each month, and then taking a long position in the highest decile firms and a short position in the lowest decile firms. The annualized return results indicate that except for 2006 and 2011 where the returns are slightly negative, the returns for all other years are positive and economically significant.

To parsimoniously test whether changes in electricity usage predict future profitability, we estimate model (1). Table 4 presents our first main result, which tests H1 based on Fama-MacBeth regressions. In Panel A, year over year monthly change in electricity usage is measured. We regress changes in ROA one quarter ahead against current changes in electricity usage for every calendar month during our sample period, and take the time-series averages of the coefficients to obtain t-statistics. In the first three columns, cross-sectional regressions are based on raw continuous variables, while the last column is based on decile ranks of each explanatory variable. We also control for a variety of firm characteristics in both panels that could potentially affect changes in future earnings.

The results reported in Panel A of Table 4 indicate that changes in current electricity usage are positively associated with subsequent earnings changes even after controlling for size, book to market, past returns, leverage, current ROA and changes in contemporaneous ROA. The economic significance is also non-trivial. Specifically, a one standard deviation increase in changes in electricity usage leads to 2.5 to 2.6% an increase in subsequent changes in ROA.

Because our dependent variable, ROA_{q+1} , is measured at a quarterly interval, we also consider year-over-year change in quarterly electricity usage as an independent variable as a robustness check. In Panel B, we measure change in electricity usage over a quarter. In other words, we report time-series average of the coefficients estimated from the 36 cross-sectional regression from 2006 Q1 to 2014 Q4. The results reported in Panel B of Table 4 mirror largely those based on monthly changes in electricity usage reported in Panel A of Table 4. These results are consistent with H1 which predicts a positive association between electricity usage and future earnings.

Thus far, we find evidence that the electricity usage growth predicts a firm's future profitability. To test the predictive ability of electricity usage in the stock market, we test whether change in electricity usage is indicative of future returns. Specifically, for every calendar month during our sample period, we regress monthly returns on previous month's changes in electricity usage and additional control variables. We then take the time-series averages and standard errors to obtain t-statistics. Similar to Table 4, the first three columns are based on raw continuous variables, while the last column is based on decile ranks to mitigate the impact of outliers. In table 5, we report the regression results with one-month ahead returns as the dependent variable. Column (1) presents the regression results of the return predictability of change in electricity usage, controlling for market beta, firm size, book-to-market and past returns. The coefficient on $\Delta ELEC_t$ is positive and significant at the 1 % level, and suggests that a positive increase (relative to the year before) in one unit of electricity usage deflated by average total asset leads to 0.5% higher return in the subsequent month. In columns (2) and (3), we include additional control variables in the regression analysis, namely $LEVERAGE_t$ and E/P_t. The coefficient estimate of $\Delta ELEC_t$ reported in column (2) continues to be positive and statistically significant at the 1% level, indicating that the return predictability of change in electricity usage holds after additionally controlling for a firm's leverage. In column (3), we continue to find that changes in electricity usage are positively associated with future returns. In the last column, we use decile-ranked variables to check the robustness of our findings to outliers, and find that the coefficient on $\Delta ELEC_t$ is positive and statistically significant with a t-statistic of 3.21. All the other control variables that are statistically significant exhibit signs in the expected directions. To summarize, the results clearly indicate that increases in electricity usage in current month leads to larger stock returns in the subsequent month, consistent with H2.

To gauge the economic significance of the relation between changes in electricity usage and future returns, we calculate returns for quintile portfolios sorted by changes in electricity usage. Specifically, for each month during our sample period, we sort all stocks in our sample based on electricity usage of the previous month. Once we obtain these monthly portfolio returns, we calculate two abnormal returns. The first is size-adjusted abnormal return, computed by subtracting off value-weighted portfolio return of firms that belong to the same size quintile. The second is also a benchmark-adjusted abnormal return, where 4*4*4 benchmark groups are constructed based on size, book to market and momentum, following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW from here on).[3]

[3] We modify the DGTW method in two ways. First, instead of ranking the stocks by their market capitalization at June 30th and using that ranks throughout the year, we rank the stocks by their market capitalization each month. Similarly, instead of using the most recent fiscal year-end book value divided by the total market capitalization of equity at the end of the December immediately prior to the ranking date and using that book-to-market ranks throughout the year, we use the most recent fiscal quarter-end book value divided by the total market capitalization of equity each month to rank stocks monthly based on the book-to-market value within the size ranks. Also, instead of sorting each size/book-to-market fractile on the 12-month past return, lagged one month on June 30th and using that ranks throughout the year, we rank the stocks each month, based on the 12-month past return lagged one month, within the size/book-to-market fractile. We modify the annual setting of DGTW to a monthly setting, because the monthly setting is by far more suitable to our monthly return analysis. Second, instead of ranking stocks in quintiles for the size, book-to-market and momentum, we rank stocks in quartiles, resulting in 4*4*4=64 DGTW groups instead of 5*5*5=125. We use quartiles instead of quintiles due to the sample size issue. Our sample consists of 33,961 firm-month observations, and our period covers 108 months from January 2006 to December 2014. Dividing 33,961 by 108, there are, on average about 314 observations per month. Therefore, if we adopt 125 groups, one

The results reported in Table 6 indicate that abnormal returns are in general higher for portfolios of firms whose change of electricity usage is larger. Specifically, size-adjusted abnormal return for the top quintile (i.e. firms with largest increases in electricity usage) is 0.259% per month, while the corresponding figure is -0.311% per month for the bottom quintile (i.e. firms with largest decreases in electricity usage), both of which are statistically significant at the 10% level. We observe a similar pattern for DGTW benchmark-adjusted abnormal returns. A hedge portfolio return obtained by buying top quintile portfolio stocks and shorting the bottom quintile portfolio stocks yields an average monthly return of 0.571% based on size benchmark and 0.404% based on DGTW benchmark, both of which are statistically significant at the 1% and 5% levels, respectively. As shown in Figure 1, we find evidence on the stability of the excess returns to the trading strategy. The hedge portfolio return is positive and significant in 7 out of the 9 years examined.

We also calculate abnormal hedge portfolio returns using the Fama-French factor model. The excess return estimates, or alphas, are obtained using monthly returns for quintiles sorted by $\Delta ELEC_t$ for the excess return model, the three-factor model, and the four-factor model, respectively. In untabulated analysis, we find that that the excess returns tend to increase as we move from the lowest quintile to the highest quintile and that the differences between the highest quintile and the lowest quintile excess returns are statistically significant. A hedge portfolio return generates an economically significant 0.56 (0.45) monthly abnormal return based on the three-factor (four-factor) model, corroborating our inferences about the association between electricity usage and future stock returns.

group, on average, will consist of about 3 firms, which is too small a number to be considered a representation of a group. DGTW excess returns are calculated as the portfolio return in excess of the value-weighted average return of firms belonging to the same DGTW group each month.

We acknowledge that one potential concern with respect to electricity usage is that it exhibits a highly seasonal pattern. Figure 2 reports average normalized electricity usage and average normalized EDD for each month. A firm's electricity usage for a given month *t* is scaled and normalized by its own annual electricity usage of the year to which month *t* belongs. The normalized electricity usage for each month is then averaged across different firms in our entire sample to yield a single representative value for each month. Figure 2 clearly indicates that electricity usage hits its peak during winter when there is a lot of heating demand. In order to illustrate the temperature movement along with the electricity usage, we calculate the energy degree days (EDD) for each month and plot the normalized EDDs in figure 2, simultaneously with the normalized electricity usage. In calculating energy degree days (EDD), we first calculate cooling degree days (CDD) defined as max[0, $\frac{T_{max}+T_{min}}{2} - 18°$], and heating degree days (HDD) defined as min[0, $18° - \frac{T_{max}+T_{min}}{2}$], where T_{max}(T_{min}) is the maximum(minimum) temperature during that month. These measures are designed to capture deviations from 18 degrees Celsius, at which energy is least consumed. We then add CDD and HDD for a given month to obtain energy degree days (EDD). As expected, figure 2 illustrates that EDDs are high during winters and summers, while they are low during springs and falls.

The seasonal effect described above motivates the need to adjust the firm-level electricity usage to weather fluctuations. Thus, in the first stage regression, we estimate the following rolling regression for the 24 months prior to month *t* to create our firm-specific measure of weather sensitivity.

$$\Delta ELEC_t = \beta 1*Temp\_Deviation*SpringFall + \beta 2*Temp\_Deviation*Summer + \beta 3*Temp\_Deviation*Winter + \beta 4*SpringFall + \beta 5*Summer + \beta 6*Winter + \varepsilon \quad (3)$$

Using the estimates from the rolling regression, we estimate the predicted weather effect by calculating the $\Delta\widehat{ELEC}_t$ for each firm month. This measure is specific to each firm month and it represents the incremental effect of year over year temperature deviation on firm-level change in electricity usage. We use past 24 months of $\Delta ELEC_t$ and weather data, and require at least 10 months of data for each firm-month regression. *Temp_Deviation* is defined as the temperature difference between current month and the same month of past year ($Temperature_t$– $Temperature_{t-12}$). *SpringFall*, *Summer* and *Winter* are indicator variables for each season to capture different implications of temperature deviation on electricity usage for each season.[4]

We report the results of the first-stage regression in Table 7, Panel A. While we obtain individual coefficient estimates and R-square values for each firm month observation, the values reported here are averaged values across each firm-month estimate. We expect the coefficient estimates on *Temp_Dev*Winter* to be negative, because during cold winter times, higher temperature relative to the same month of prior year would mean less need for heating, and consequently, reduced level of electricity usage. On the other hand, we expect a positive coefficient on *Temp_Dev*Summer* because during hot summer days, higher temperature relative to the same month of prior year would lead to more air-conditioning and increase the level of electricity usage. The signs of the coefficients on *Temp_Dev*SpringFall* are harder to anticipate ahead of time, although the unusually high normalized electricity usage during winter months

[4] Firm months ending in Jan-Mar are considered to be winter and firm months ending in July-Sep are considered to be summer. The rest of the firm months, i.e., firm months ending in Apr-June and Oct-Dec are considered to be spring and fall.

plotted in Figure 2 suggests that electricity is a more important source of heating than cooling, and hence a positive temperature deviation is more likely to reduce the electricity usage than increase it.

As expected, the coefficient estimates on *Temp_Deviation*SpringFall* and *Temp_Deviation*Winter* are negative and statistically significant, and the magnitude of the coefficient estimate, in absolute terms, is greater during winter months than during spring and fall months. Furthermore, although the coefficient estimate on *Temp_Deviation*Summer* is negative, it is insignificant with a t-statistic of 0.66.

Using the estimates from the first-stage regression, we obtain the weather-adjusted $\Delta\widehat{ELEC}_t$, that is, the fitted value for each firm month observation. The difference between actual $\Delta ELEC_t$ and the fitted $\Delta\widehat{ELEC}_t$ is defined as $\Delta ELEC_t$(residual). We then use these residuals as regressors in the second stage regression to predict the next month's stock returns. The results, reported in Panel B of Table 7 indicate that changes in electricity usage, after netting out the effect of temperature changes, still predict future stock returns. $\Delta ELEC_t$(residual) continues to be positive and statistically significant, and the relationship holds regardless of our choice of control variables.

In summary, the results reported in Table 7 suggest that return predictability of electricity usage still holds after controlling for any seasonal effect.

In Table 8, we implement two sets of additional robustness tests. In Panel A of Table 8, we consider an alternative measure of changes in electricity. Instead of scaling the difference by total assets, we scale it by electricity usage in the same month of the previous year. This scaling effectively yields a growth rate in electricity usage against the same month of the previous year. The results indicate that the positive correlation between electricity usage and future stock returns still holds under this alternative definition of electricity usage. In fact, the magnitudes of the coefficients are slightly larger than those reported in Table 5.

In Panel B of Table 8, we include an additional control variable, namely, changes in industry-level electricity usage. Specifically, we take the average changes in electricity across all firms within the same industry in a given month, where industries are classified based on the KISVALUE database mid-level industry classification (comparable to 2-digit SIC code classification). The results again suggest that changes in electricity are positively correlated with future stock returns even after controlling for changes in industry-level changes in electricity.

To gain further insight into the relation between electricity usage and future returns, we split firms into two groups based on the degree of information asymmetry and examine whether the relation differs between the two groups. It is likely that investors find it hard to collect and process information for firms with greater information asymmetry. If investors do not fully incorporate and underreact to the extent to which changes in electricity usage signal future earnings for opaque firms, we thus expect that the mispricing of electricity usage will be more pronounced for firms with greater information asymmetry. We consider proxies for information asymmetry such as firm size (market cap), R&D (research and development expense scaled by sales), and firm age (number of months since a firm's stock is first traded in the stock market). To the extent that the predictability is attributed to market participants mispricing of electricity usage, we anticipate that the relation between the change of electricity usage and future returns will be more pronounced in firms with greater information asymmetry (i.e., small firms, high R&D firms, and young firms). We report the results in Table 9. Consistent with our expectation, we find that the positive association between changes in electricity and future stock returns is largely driven by high information asymmetry firms such as small firms, high R&D firms, and young firms.

In the first two columns, we report regression results for subsamples of firms divided based on the firm size. $\Delta ELEC_t$ has a strong return-predictive power for subsample of firms whose firm sizes are smaller than the median value, as the coefficient estimate on $\Delta ELEC_t$ for this subsample is positive and statistically significant at the 1% level with a t-statistic of 2.62. On the contrary, for subsample of firms that belong to the bigger half in terms of firm size, $\Delta ELEC_t$ does not seem to have any incremental explanatory power as its coefficient estimate is statistically insignificant. The third and fourth columns report regression results for subsamples of firms with R&D expenditure (relative to sales) higher and lower than the median value. We find that the return predictability of $\Delta ELEC_t$ is more pronounced for high R&D firms with greater information asymmetry. Specifically, we observe that the coefficient estimate on $\Delta ELEC_t$ is greater in magnitude and statistically more significant for high R&D firms (estimate = 0.007, t-stat = 2.71) than for low R&D firms (estimate = 0.002, t-stat = 0.98). In the last two columns, we run separate regressions for young firms with high information asymmetry and for old firms with low information asymmetry. The coefficient on $\Delta ELEC_t$ is 0.007 (t-statistics = 3.05) for young firms and 0.003 (t-statistics = 1.34) for old firms, again corroborating that the predictability of $\Delta ELEC_t$ is stronger for firms with greater information asymmetry.

Overall, these findings suggest that investors do not recognize the implications of electricity usage growth for future profitability and are slow in impounding the information in stock prices.

5. Summary and conclusions

Despite great interest in evaluating firms' non-financial indicators for operating performances, there is little evidence regarding the impact of a firm's real production activities on firm performance. In this paper, we propose that changes in a firm's real activities predict a firm's future performance.

By using a novel institutional setting for Korean firms, we examine the underlying relation between a firm's electricity usage growth rate and future earnings changes and future returns. In other words, we study whether change in electricity usage is informative about future profitability and market participants fully recognize the implication of the change for subsequent accounting profitability.

Our empirical analyses to examine the impact of electricity usage growth on future profitability and returns are based on a large sample Korea firms for the period of 2006-2014, As expected, we find that changes in a firm's electricity usage have incremental ability to predict subsequent earnings changes, implying that firms which increased (decreased) electricity usage exhibit higher earnings (lower) in the future. We find that this predictive power of electricity usage change is not subsumed by other firm characteristics and fundamental signals that may affect future performance. More important, we find that unexpected increases are associated with substantial future abnormal returns, even after controlling for various risk factors. Together with the existence of long-run abnormal returns, we also find that the relation between changes in electricity usage and long-term abnormal returns is pronounced in firms with greater information asymmetries. These results are consistent with the market's mispricing of electricity usage. Investors do not appear to quickly impound information on electricity usage into stock prices.

Overall, we find that electricity usage is value-relevant in that it incrementally predicts future profitability and stock performance. Our evidence highlights the importance of electricity usage in a capital research context and underscores the role of non-financial leading indicators for firm valuation.

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FIGURE 1
Annualized Hedge Portfolio Return

The figure below shows hedge portfolio returns from taking a long position in the highest $\Delta ELEC_t$ decile and a short position in the lowest $\Delta ELEC_t$ decile. The monthly hedge portfolio returns are calculated by subtracting the monthly averaged return of the lowest decile portfolio from the monthly average return of the highest decile portfolio.

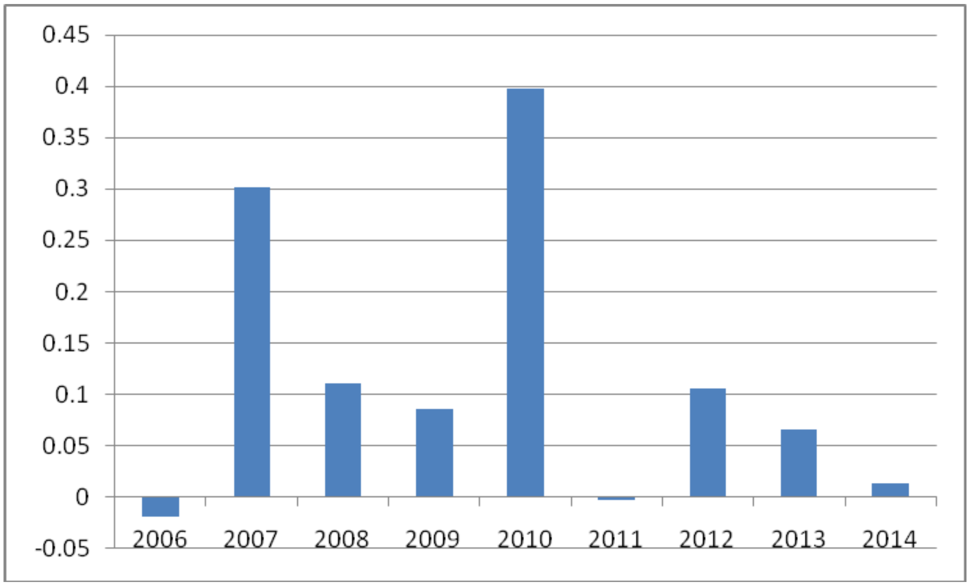

Figure 1

Figure 1 presents annualized hedge portfolio returns by forming deciles based on changes in electricity usage scaled by average total asset. The annualized hedge portfolio returns were calculated by summing the 12 monthly hedge portfolio returns each year.

FIGURE 2

Normalized Electricity Consumption and Weather, Monthly

The figure shows normalized electricity usage and weather conditions. We obtain electricity usage from the KEPCO. Weather data are obtained from the NCDSS. Normalized electricity usage is monthly consumption divided by the annual consumption for each firm over the sample period, averaged for each month. Normalized EDD is the average energy degree days (EDD) for each month over the same period. EDDs are the sum of normalized cooling degree days (CDD) and normalized heating degree days (HDD) divided by 2 so that it sums to 1 each year.

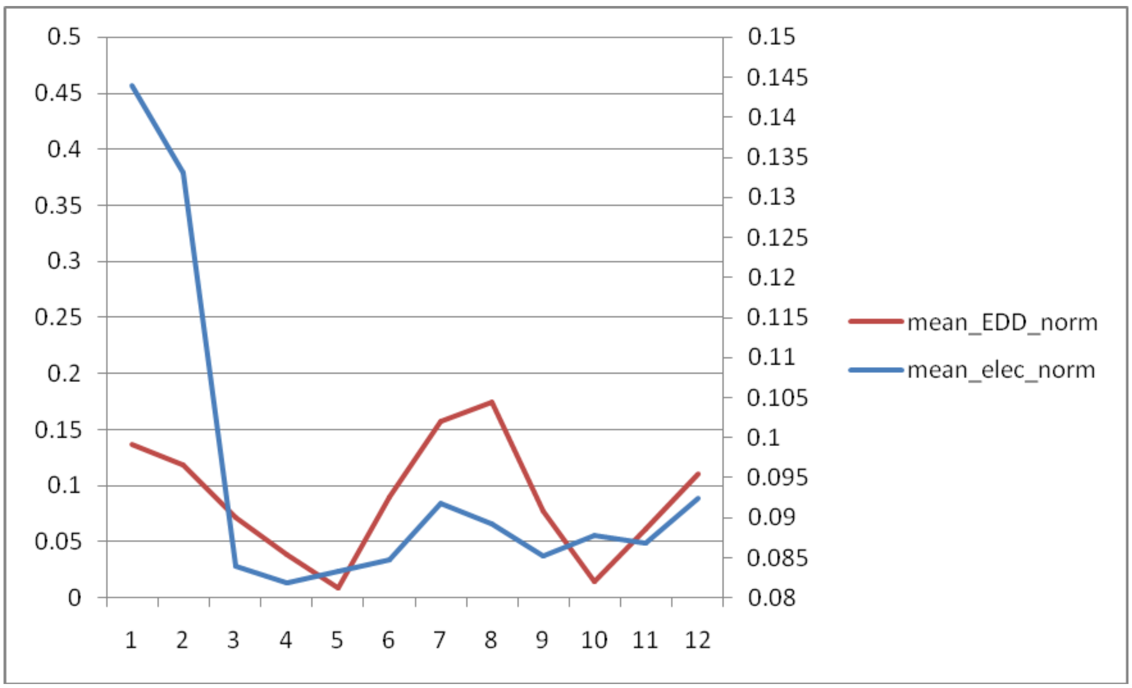

TABLE 1

Sample Selection

This table presents information on the sample selection procedure. Our sample includes 34,207 firm-months of 433 firms for the period of 2006-2014.

Sample Selection filters	# of Obs.
Initial Sample:	231,246 branch-months
Merge into firm-months	53,292 firm-months
Firms whose standard deviation of electricity usage is less than 1	52,309 firm-months
Firm-months with returns and electricity change variables	37,089 firm-months
Firm-months with control variables	35,153 firm-months
Firms that have been listed for at least 6 months	34,207 firm-months
Remaining Sample:	34,207 firm-months

TABLE 2
Descriptive Statistics

This table presents summary statistics for the variables used in our analyses. Detailed definitions of variables are included in APPENDIX. $\Delta ELEC_t$ and RET_{t+1} are winsorized each month at the bottom and top 1% percentiles. We report descriptive statistics of the main variables and control variables used in the analysis using the Fama-Macbeth approach. The sample consists of 34,207 firm-month observations from January 2006 to December 2014.

Variable	N	MEAN	STD	P25	P50	P75
Main Variables						
$\Delta ELEC_t$	108	0.077	0.102	0.020	0.081	0.143
RET_{t+1}	108	0.011	0.064	-0.024	0.011	0.043
ΔROA_{q+1}	105	-0.102	0.664	-0.455	-0.252	0.072
Control Variables						
$BETA_t$	108	0.994	0.067	0.915	1.030	1.048
$SIZE_t$	108	1.517	0.304	1.321	1.440	1.552
BTM_t	108	0.818	0.085	0.781	0.819	0.857
$PASTRET_{[t-12,t-1]}$	108	0.187	0.303	0.029	0.112	0.299
$LEVERAGE_t$	108	2.916	0.276	2.677	2.888	3.174
E/P_t	108	0.070	1.092	-0.240	0.379	0.663
ΔROA_q	108	-0.102	0.658	-0.441	-0.245	0.042
ROA_q	108	0.831	0.577	0.468	0.947	1.182
D_LOSS_t	108	0.245	0.092	0.166	0.252	0.297

TABLE 3
Correlations

This table presents Pearson correlations for the variables used in our analyses. Detailed definitions of variables are included in APPENDIX. We use a Fama-Macbeth approach in calculating the correlations among variables in order to achieve consistency with our later regression analysis. In effect, we exploit the 108 monthly observations from January 2006 to December 2014. Significance levels are presented in italics below the correlations.

	1	2	3	4	5	6	7	8	9	10	11	12
1. $\Delta ELEC_t$	1.0000											
2. RET_{t+1}	0.0119	1.0000										
	0.0701											
3. ΔROA_{q+1}	0.0292	0.0512	1.0000									
	0.0000	*0.0000*										
4. $BETA_t$	0.0113	-0.0218	-0.0200	1.0000								
	0.0766	*0.1370*	*0.0092*									
5. $SIZE_t$	-0.0137	-0.0141	-0.0129	0.0564	1.0000							
	0.1082	*0.2405*	*0.0842*	*0.0000*								
6. BTM_t	-0.0195	0.0675	0.0469	-0.0858	-0.4301	1.0000						
	0.0060	*0.0000*	*0.0000*	*0.0000*	*0.0000*							
7. $PASTRET_{[t-12,t-1]}$	0.0495	0.0098	-0.0043	-0.0627	0.0720	-0.2476	1.0000					
	0.0000	*0.4627*	*0.6915*	*0.0003*	*0.0000*	*0.0000*						
8. $LEVERAGE_t$	0.0096	0.0058	-0.0337	-0.0690	0.3512	0.0400	0.0302	1.0000				
	0.1532	*0.5334*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0009*					
9. E/P_t	0.0102	0.0276	0.0221	-0.0138	0.2506	-0.0481	0.0814	0.0873	1.0000			
	0.0205	*0.0138*	*0.0212*	*0.1241*	*0.0000*	*0.0000*	*0.0000*	*0.0000*				
10. ΔROA_q	0.0556	0.0633	0.1574	-0.0271	-0.0091	0.0288	0.0744	-0.0251	0.1184	1.0000		
	0.0000	*0.0000*	*0.0000*	*0.0007*	*0.2318*	*0.0000*	*0.0000*	*0.0007*	*0.0000*			
11. ROA_q	0.0636	0.0707	0.0820	-0.1235	0.1912	-0.1159	0.2093	0.1279	0.2503	0.5654	1.0000	
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*		
12. D_LOSS_t	-0.0426	-0.0645	-0.0706	0.0986	-0.1696	0.0793	-0.1459	-0.1491	-0.2272	-0.2644	-0.5586	1.0000
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	

TABLE 4

Predicting Future Earnings with Changes in Electricity Usage

This table reports the estimates from the Fama-MacBeth regression of subsequent quarter's year over year ROA change (ΔROA_{q+1}) on changes in electricity usage and firm characteristics. The coefficient estimates are the time-series average of the coefficients estimated from the 108 cross-sectional regressions from January 2006 to December 2014 for Panel A results, and the time-series average of the coefficients estimated from the 36 cross-sectional regressions from 2006 Q1 to 2014 Q4 for Panel B results. The sample consists of firm-months with electricity usage data from KEPCO. All variables are described in the Appendix and collected from the FNDATAGUIDE database. Rank variables are raw variables ranked into deciles(0,9) each month and divided by nine so that each signal observation takes on a value ranging between zero and one. Numbers in parentheses are *t*-statistics computed as the ratio of the mean of the coefficients from monthly cross-sectional regressions to the standard error of the coefficients' distribution. In Panel A, ΔROA_{q+1} is regressed on the year over year monthly changes in electricity usage and other control variables. The dependent variable, ΔROA_{q+1}, is defined as the net income divided by the beginning of the quarter total assets, multiplied by 100, where *q* indicates the quarter to which the month t belongs and *q+1* indicates the subsequent quarter. All variables are described in the Appendix. Column (1), (2) and (3) report results from the OLS regression and column (4) reports regression results on decile-ranked independent variables. In Panel B, ΔROA_{q+1} is regressed on the year over year quarterly changes in electricity usage and firm characteristics. The dependent variable, ΔROA_{q+1}, is defined as the net income of the subsequent quarter, divided by the beginning of the period total assets, multiplied by 100. All variables are described in the Appendix. Column (1), (2) and (3) report results from the OLS regression and column (4) reports regression results on decile-ranked independent variables.

Panel A: Predicting Future Earnings with Changes in Monthly Electricity Usage

	(1)	(2)	(3)	(4)
Independent variables	OLS	OLS	OLS	Rank
Intercept	-0.045	-0.067	0.026	-1.140***
	(-0.22)	(-0.33)	(0.14)	(-6.10)
$\Delta ELEC_t$	0.258***	0.247***	0.241***	0.217***
	(3.87)	(3.74)	(3.62)	(2.70)
$SIZE_t$	0.056***	0.059***	0.051***	0.073
	(3.05)	(3.34)	(3.07)	(0.89)
BTM_t	0.397***	0.413***	0.419***	0.357***
	(3.92)	(3.92)	(3.94)	(3.38)
$PASTRET_{[t-12,t-1]}$	-0.118	-0.080	-0.088	-0.310***
	(-1.08)	(-0.75)	(-0.83)	(-2.64)
$LEVERAGE_t$	-0.164***	-0.159***	-0.157***	-0.423***
	(-4.68)	(-4.68)	(-4.91)	(-4.75)
ΔROA_q	0.173***	0.186***	0.193***	1.841***
	(8.94)	(8.67)	(9.09)	(13.18)
ROA_q		-0.008	-0.027	0.309***
		(-0.46)	(-1.30)	(2.72)
D_LOSS_t			-0.207**	0.102
			(-2.25)	(1.17)
R^2	8.248	9.666	10.481	8.719

Panel B: Predicting Future Earnings with Changes in Quarterly Electricity Usage

Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) Rank
Intercept	0.004	-0.015	0.074	-1.078***
	(0.01)	(-0.04)	(0.22)	(-3.19)
$\Delta ELEC_{qtr}$	0.105***	0.101***	0.100***	0.269**
	(2.83)	(2.83)	(2.75)	(2.19)
$SIZE_t$	0.062*	0.062**	0.053*	0.082
	(1.94)	(2.03)	(1.86)	(0.65)
BTM_t	0.334*	0.342*	0.350*	0.317*
	(1.92)	(1.89)	(1.92)	(1.79)
$PASTRET_{[t-12,t-1]}$	-0.280	-0.265	-0.273	-0.507**
	(-1.44)	(-1.40)	(-1.48)	(-2.45)
$LEVERAGE_t$	-0.165**	-0.160**	-0.157***	-0.404**
	(-2.50)	(-2.48)	(-2.58)	(-2.52)
ΔROA_q	0.173***	0.183***	0.191***	1.831***
	(5.24)	(5.12)	(5.40)	(7.51)
ROA_q		0.000	-0.018	0.363*
		(0.00)	(-0.48)	(1.69)
D_LOSS_t			-0.200	0.107
			(-1.20)	(0.67)
R^2	8.003	9.353	10.229	8.803

TABLE 5

Return Predictability of Changes in Electricity Usage

This table reports the estimates from the Fama-MacBeth regression of one-month-ahead returns on changes in electricity usage and firm characteristics. The coefficient estimates are the time-series average of the coefficients estimated from the 108 cross-sectional regressions from January 2006 to December 2014. The sample consists of firm-months with electricity usage data from KEPCO. Return data are collected from the KISVALUE database and other control variables are collected from the FNDATAGUIDE database. All variables are described in the Appendix. Column (1), (2) and (3) report results from the OLS regression and column (4) reports regression results on decile-ranked independent variables. Rank variables are raw variables ranked into deciles(0,9) each month and divided by nine so that each signal observation takes on a value ranging between zero and one. Numbers in parentheses are *t*-statistics computed as the ratio of the mean of the coefficients from monthly cross-sectional regressions to the standard error of the coefficients' distribution.

Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) Rank
Intercept	-0.011*	-0.009	-0.008	-0.016**
	(-1.88)	(-1.39)	(-1.29)	(-2.39)
$\Delta ELEC_t$	0.005***	0.005***	0.005***	0.007***
	(2.73)	(2.80)	(2.77)	(3.21)
$BETA_t$	-0.001	-0.001	-0.002	-0.002
	(-0.35)	(-0.36)	(-0.39)	(-0.46)
$SIZE_t$	0.001	0.001	0.000	-0.013***
	(0.58)	(0.90)	(0.37)	(-2.73)
BTM_t	0.024***	0.024***	0.024***	0.022***
	(6.42)	(6.50)	(6.81)	(5.42)
$PASTRET_{[t-12,t-1]}$	0.007**	0.007***	0.007**	0.005
	(2.52)	(2.60)	(2.57)	(1.08)
$LEVERAGE_t$		-0.001	-0.001	-0.001
		(-1.21)	(-1.25)	(-0.29)
E/P_t			0.001***	0.036***
			(3.45)	(11.37)
R^2	7.133	7.690	8.743	8.980

TABLE 6

Abnormal Hedge Portfolio Returns to Changes in Electricity Usage Strategy

This table reports abnormal hedge portfolio returns to changes in electricity usage. We report size-adjusted abnormal returns and DGTW abnormal returns for quintile portfolios formed based on the change of electricity usage deflated by assets. Size-adjusted returns are computed each month by measuring the portfolio return in excess of the return on a value-weighted portfolio of firms that belong to the same size quintile. DGTW excess returns are calculated as the portfolio return in excess of the value-weighted average return of firms belonging to the same DGTW group each month. The sample is divided into 64 DGTW groups based on the size, book-to-market, and momentum. Mean excess returns are calculated for each month, and then averaged across the quintiles, i.e. a Fama-Macbeth approach is used in the analysis.

Size-Adjusted Abnormal Returns						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5 – Q1
Mean	-0.0031**	-0.0001	0.0025**	0.0021	0.0026*	0.0057***
t-stat	(-2.24)	(-0.04)	(2.07)	(1.52)	(1.77)	(2.82)
DGTW Abnormal Returns						
	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5 – Q1
Mean	-0.0020	-0.0007	0.0012	0.0027**	0.0021*	0.0040**
t-stat	(-1.57)	(-0.57)	(1.13)	(2.32)	(1.70)	(2.28)

TABLE 7

Return Predictability of Changes in Electricity Usage – Weather-adjusted Usage

This table reports regression results after adjusting the electricity usage to weather fluctuations. In the first stage regression, we estimate the following rolling regression for the 24 months prior to month *t* to create our firm-specific measure of weather sensitivity.

$$\Delta ELEC_t = \beta1*Temp\_Deviation*SpringFall + \beta2*Temp\_Deviation*Summer + \beta3*Temp\_Deviation*Winter + \beta4*SpringFall + \beta5*Summer + \beta6*Winter + \varepsilon$$

This measure is specific to each firm month. We use past 24 months of $\Delta ELEC_t$ and weather data, and require at least 10 months of data for each firm-month regression. *Temp_Deviation* is defined as the temperature difference between current month and the same month of past year ($Temperature_t$–$Temperature_{t-12}$). *SpringFall*, *Summer* and *Winter* are indicator variables for each season to capture different implications of temperature deviation on electricity usage for each season. This regression estimates the incremental effect of year over year temperature deviation on firm-level change in electricity usage. Panel A reports the first-stage regression results. While we obtain individual coefficient estimates and R-square values for each firm month observation, the values reported here are averaged values across each firm-month estimate. Using the estimates from the first-stage regression, we obtain the weather-adjusted $\Delta ELEC_t$, that is, the fitted value for each firm month observation. The difference between actual $\Delta ELEC_t$ and the fitted $\Delta ELEC_t$ is defined as $\Delta ELEC_t$(residual). In the second stage regression, we use $\Delta ELEC_t$(residual) as the main independent variable in our return analysis. $\Delta ELEC_t$(residual) are winsorized at the bottom and top 1% percentiles every month to exclude the effect of outliers. Panel B reports the second-stage regression results.

Panel A: First-stage Regressions

	(1)
Independent variables	
*Temp_Deviation*SpringFall*	-0.041***
	(-18.04)
*Temp_Deviation*Summer*	-0.002
	(-0.66)
*Temp_Deviation*Winter*	-0.063***
	(-26.14)
SpringFall	0.088***
	(44.48)
Summer	0.100***
	(43.13)
Winter	0.103***
	(43.45)
R^2 (average)	0.5079

Panel B: Second-stage Regressions

Independent variables	(1)	(2)	(3)
Intercept	-0.008	-0.006	-0.005
	(-1.35)	(-0.91)	(-0.76)
$\Delta ELEC_t$(residual)	0.004**	0.004**	0.004**
	(2.17)	(2.14)	(2.03)
$BETA_t$	-0.001	-0.001	-0.001
	(-0.25)	(-0.25)	(-0.26)
$SIZE_t$	0.000	0.001	-0.000
	(0.21)	(0.50)	(-0.06)
BTM_t	0.022***	0.022***	0.021***
	(5.50)	(5.51)	(5.70)
$PASTRET_{[t-12,t-1]}$	0.066**	0.007**	0.006**
	(2.08)	(2.15)	(1.98)
$LEVERAGE_t$		-0.001	-0.001
		(-1.17)	(-1.17)
E/P_t			0.001***
			(3.69)
R^2	7.493	8.107	9.301

TABLE 8

Robustness Tests

This table reports robustness tests performed in addition to the main results reported in Table 6. Panel A reports the estimates from the Fama-MacBeth regression of one-month-ahead returns on changes in electricity usage and firm characteristics. Year over year monthly electricity usage growth rate is used as a main independent variable ($\Delta ELEC_{gr}$). Column (1), (2) and (3) report results from the OLS regression and column (4) reports regression results on decile-ranked independent variables. Rank variables are raw variables ranked into deciles(0,9) each month and divided by nine so that each signal observation takes on a value ranging between zero and one. Numbers in parentheses are *t*-statistics computed as the ratio of the mean of the coefficients from monthly cross-sectional regressions to the standard error of the coefficients' distribution. Panel B reports the estimates from the Fama-MacBeth regression of one-month-ahead returns on changes in electricity usage and firm characteristics when industry electricity usage change ($\Delta ELEC\_IND_t$) is included as an additional control variable. $\Delta ELEC\_IND_t$ is the average $\Delta ELEC_t$ across firms in the same industry calculated each month. Industries are classified based on the KISVALUE database mid-level industry classification (0A1132).

Panel A: Alternative Measures for Changes in Electricity Usage

Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) Rank
Intercept	-0.011**	-0.009	-0.008	-0.016**
	(-1.99)	(-1.49)	(-1.38)	(-2.32)
$\Delta ELEC_{gr}$	0.007***	0.008***	0.007***	0.006***
	(3.07)	(3.18)	(3.07)	(2.81)
$BETA_t$	-0.001	-0.001	-0.001	-0.002
	(-0.29)	(-0.30)	(-0.33)	(-0.42)
$SIZE_t$	0.000	0.001	0.000	-0.013***
	(0.50)	(0.84)	(0.29)	(-2.73)
BTM_t	0.025***	0.025***	0.025***	0.022***
	(6.54)	(6.60)	(6.90)	(5.43)
$PASTRET_{[t-12,t-1]}$	0.007**	0.007***	0.007***	0.005
	(2.54)	(2.62)	(2.58)	(1.10)
$LEVERAGE_t$		-0.001	-0.001	-0.001
		(-1.28)	(-1.30)	(-0.31)
E/P_t			0.001***	0.036***
			(3.53)	(11.36)
R^2	7.197	7.756	8.807	8.954

Panel B: Additional Control Variable

Independent variables	(1) OLS	(2) OLS	(3) OLS	(4) Rank
Intercept	-0.011*	-0.009	-0.08	-0.016**
	(-1.93)	(-1.44)	(-1.36)	(-2.29)
$\Delta ELEC_t$	0.004**	0.004**	0.004**	0.006***
	(2.46)	(2.53)	(2.48)	(3.40)
$BETA_t$	-0.002	-0.002	-0.002	-0.003
	(-0.48)	(-0.49)	(-0.52)	(-0.55)
$SIZE_t$	0.001	0.001	0.000	-0.013***
	(0.65)	(0.99)	(0.48)	(-2.74)
BTM_t	0.024***	0.025***	0.024***	0.021***
	(6.50)	(6.62)	(7.00)	(5.40)
$PASTRET_{[t-12,t-1]}$	0.007**	0.007**	0.007**	0.005
	(2.49)	(2.57)	(2.52)	(1.03)
$LEVERAGE_t$		-0.001	-0.001	-0.001
		(-1.23)	(-1.26)	(-0.41)
E/P_t			0.001***	0.036***
			(3.38)	(11.20)
$\Delta ELEC\_IND_t$	0.006	0.006	0.007	0.001
	(0.79)	(0.84)	(0.97)	(0.28)
R^2	7.793	8.337	9.371	9.565

TABLE 9

Return Predictability of Changes in Electricity Usage by Firm Characteristics

This table reports the estimates from the Fama-MacBeth regression of one-month-ahead returns on changes in electricity usage and firm characteristics for the subsamples partitioned by the degree of information asymmetry. We partition the sample firms into those with high and low information asymmetry based on the sample median of each information asymmetry variable (i.e., firm size, R&D expense divided by sales, and firm age). The dependent variable is one-month-ahead stock return (RET_{t+1}). All variables are described in the appendix. Numbers in parentheses are *t*-statistics computed as the ratio of the mean of the coefficients from monthly cross-sectional regressions to the standard error of the coefficients' distribution.

Independent	Size		R&D		Age	
variables	Small	Large	High	Low	Young	Old
Intercept	0.000	-0.007	-0.007	-0.010	-0.010	-0.013*
	(0.05)	(-0.93)	(-1.08)	(-1.36)	(-1.42)	(-1.90)
$\Delta ELEC_t$	0.005***	0.004	0.007***	0.002	0.007***	0.003
	(2.62)	(1.19)	(2.71)	(0.98)	(3.05)	(1.34)
$BETA_t$	0.004	-0.003	-0.001	-0.002	-0.004	0.003
	(0.98)	(-0.58)	(-0.15)	(-0.57)	(-0.92)	(0.63)
$SIZE_t$	-0.020***	-0.000	-0.000	0.001	0.001	0.000
	(-3.00)	(-0.05)	(-0.39)	(0.37)	(1.09)	(0.01)
BTM_t	0.029***	0.020***	0.023***	0.025***	0.031***	0.021***
	(6.35)	(4.39)	(5.55)	(5.78)	(6.93)	(5.39)
$PASTRET_{[t-12,t-1]}$	0.004	0.009**	0.008**	0.006	0.009**	0.005
	(1.06)	(2.50)	(2.33)	(1.50)	(2.52)	(1.61)
$LEVERAGE_t$	-0.005***	0.001	-0.001	-0.001	-0.001	-0.000
	(-2.77)	(0.73)	(-0.51)	(-0.92)	(-0.61)	(-0.22)
E/P_t	0.005***	0.001**	0.001**	0.001**	0.000	0.001***
	(5.25)	(2.43)	(2.52)	(2.53)	(0.99)	(3.56)
R^2	10.98	13.46	11.50	11.54	10.98	11.75

APPENDIX
Definitions of Variables

This appendix lists the variables used in the tables. All of the variables are estimated at the same month-end unless otherwise noted.

Variable name	Definition
ΔROA_{q+1}	Subsequent quarter's year over year changes in ROA, i.e. ROA_{q+1}-ROA_{q-3}, where *q* is the quarter to which the month *t* belongs
RET_{t+1}	One-month-ahead stock return of a firm
$\Delta ELEC_t$	Year over year changes in a firm's monthly electricity usage deflated by average total asset
$\Delta ELEC_{gr}$	Monthly electricity usage (year over year) growth rate
$\Delta ELEC\_IND_t$	The average $\Delta ELEC_t$ across firms in the same industry calculated each month where industries are classified based on the KISVALUE database mid-level industry classification (0A1132)
$\Delta ELEC_t$ (residual)	The difference between actual $\Delta ELEC_t$ and the fitted $\Delta\widehat{ELEC}_t$, where $\Delta\widehat{ELEC}_t$ is obtained using estimates from regression model (3)
$BETA_t$	Market beta calculated over previous 60 months
$SIZE_t$	The natural logarithm of 1 + a firm's market capital divided by 100,000
BTM_t	The natural logarithm of 1 + a firm's book value of equity to market value of equity
$PASTRET_{[t-12,t-1]}$	Monthly compounded return of a firm for period [t-12,t-1]
$LEVERAGE_t$	The natural logarithm of a firm's total asset deflated by book value of equity
E/P_t	A firm's net income at the beginning of the quarter divided by the end price of the firm's stock divided by 1000
ΔROA_q	Current quarter's year over year changes in ROA, i.e. ROA_q-ROA_{q-4}, where *q* is the quarter to which the month *t* belongs
ROA_q	Net income of the quarter to which the month t belongs, divided by the beginning of the quarter total assets, multiplied by 100
D_LOSS_t	An indicator variable equal to one for firms reporting a loss in the quarter to which the month *t* belongs, and zero otherwise
EDD	The sum of cooling degree days (CDD) and heating degree days

	(HDD). CDD is defined as CDD = max[0, $\frac{T_{max}+T_{min}}{2} - 18°$]. HDD is defined as HDD = min[0, $18° - \frac{T_{max}+T_{min}}{2}$]. T_{max}(T_{min}) is the monthly maximum(minimum) temperature
Temp_Deviation	The temperature difference between current month and the same month of past year, i.e. $\text{Temperature}_t - \text{Temperature}_{t-12}$
R&D	R&D expense (zero for missing values) divided by sales
Age	The number of months since a firm’s stock is first traded in the market