The predictive power of industrial electricity usage revisited: evidence from non-parametric causality tests

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Abstract

Recent research shows that the industrial electricity usage growth rate carries predictive ability over stock market returns up to 1 year. Using the recently developed non-parametric causality tests we show that the predictive power of industrial electricity usage can be explained by an ‘industry effect’ that is transmitted via the volatility channel. We argue that the countercyclical premium associated with industrial electricity usage growth is driven by the industry components that drive stock reversals, thus resulting in the negative relationship between today’s industrial electricity usage and stock market returns in the future. The findings are in line with the notion that the returns on industry portfolios are informative about macroeconomic fundamentals and suggest that the informational value of industrial electricity usage as a business cycle variable may be an artefact of return reversals driven by past industry performance.

1. Introduction

The predictive power of energy prices over the stock market has been the focus of numerous studies in the literature. Recently, Da *et al.* (2017) propose a new, energy market-based predictor for stock returns and show that the industrial electricity usage growth rate can predict stock market returns up to 1 year, while it tracks the output of the most cyclical sectors. Given that electricity cannot easily be stored, Da *et al.* (2017) suggest that industrial electricity usage can be used to track production and output in real time and thus, provides a reliable measure of economic growth, which in turn drives its predictive power over stock market returns. Another strand of the literature, however, suggests that certain industries can predict aggregate stock market movements (e.g. Hong *et al.*, 2007) even after controlling for various risk proxies and liquidity, while Tse (2015) recently presents evidence to the contrary with fewer industries possessing predictive power over stock market returns. Given these findings, a natural research question is whether the predictive power of industrial electricity usage is a manifestation of certain industries leading the stock market or whether this new, energy-based predictor indeed possesses market-wide predictive power, beyond industrial classifications, which would then have significant implications for active portfolio strategies.

The main contribution of this study is to link the two strands of the literature, i.e. stock market predictability and whether industries lead the stock market, in a novel context and to examine whether the predictive ability of industrial electricity usage is driven by a possible 'industry effect' in which particular industries lead the stock market. If the predictive power of industrial electricity usage is indeed driven by the leading role of particular industries over the aggregate stock market, then this would be further evidence towards industry-level dynamics containing fundamental information regarding aggregate stock market movements. It would also imply that the risk premium associated with the industrial electricity usage, as documented by Da *et al.* (2017), is an artefact of the 'industry effect' on stock market returns and one has to instead focus on those industries that drive long-term return reversals in the stock market. This would then imply profitable contrarian strategies involving those industries that serve as the basis for such a countercyclical risk premium. Clearly, the analysis is not only a matter of practical importance from an investment perspective but also provides insight to the informational efficiency of the stock market as predictability via industry returns would imply inefficiencies in the diffusion of information across industries and the aggregate market.

Consistent with Da *et al.* (2017), we find significant causal links between industrial electricity usage and monthly returns for 28 of 32 industries examined. Interestingly, causality is found to be stronger when industry returns are adjusted for market and other risk factors, suggesting that industry-specific fundamentals may play a role in the predictive ability of industrial electricity usage on stock returns. The "industry effect" is further supported by the causality tests on the realised volatility of industry returns. Despite the finding of a significant causality from industrial electricity usage to realised volatility consistently across all industries when raw industry returns are examined, the causality effect on volatility becomes limited to only a handful of industries when the well-known risk proxies are controlled for. Consequently, we argue that there is indeed an 'industry effect' driving the predictive ability of industrial electricity usage which becomes evident when industry returns are adjusted for systematic risk factors. Furthermore, our findings imply that this "industry effect" is transmitted via the volatility channel, rather than returns, implying the ability of particular industries to serve as risk proxies that may provide information regarding future economic fundamentals.

Examining alternative portfolio sorts based on firm size and book-to-market ratio, we find that the predictive ability of industrial electricity usage is largely driven by big firms with low book-to-market ratios. Considering the recent finding by Wu and Mazouz (2016) that industry reversals are driven by big firms and value stocks in those industries, we argue that the countercyclical premium associated with industrial electricity usage growth is in part driven by the industry components that drive stock reversals, thus resulting in the negative relationship between today's industrial electricity usage and stock returns in the future. In all, our findings suggest that the predictive ability of industrial electricity usage may be primarily driven by an 'industry effect' that drives return reversals in the stock market and the finding that industrial electricity usage serves as a business cycle variable may simply be an artefact of return reversals driven by past industry performance.

The rest of the paper is organised as follows: Section 2 provides a brief review of the related literature while Section 3 presents the methodology for the non-linear causality test employed. The data and the empirical findings are provided in Section 4. Finally, Section 6 concludes.

2. Literature review

Stock market predictability is examined in numerous studies with various financial and economic variables tested for their predictive ability for stock market movements (e.g. Ang and Bekaert, 2007; Boudoukh *et al.*, 2008; Welch and Goyal, 2008; Rapach and Zhou, 2013). In more recent studies, a number of variables including divergent beliefs among fund managers (Jiang and Sun, 2014), investor sentiment (Da *et al.*, 2015; Huang *et al.*, 2015), short interest (Rapach *et al.*, 2016) have been documented to command predictive ability over stock market returns and/or crashes. Recently, Da *et al.* (2017) propose a new, energy market-based predictor and show that the industrial electricity usage growth rate can predict stock market returns up to 1 year, while it tracks the output of the most cyclical sectors. Advocating industrial electricity usage as a business cycle variable, Da *et al.* (2017) show that high industrial electricity usage predicts lower stock returns in the future, implying a countercyclical risk premium associated with this variable.

In a separate strand of the literature, the informational content of industry returns for stock market forecasting has been examined, without a clear consensus on the direction of predictability. In a well-cited study, Hong *et al.* (2007) find that 14 of 34 US industries can predict stock market movements, even after controlling for various risk proxies and liquidity. Extending the role of industries to asset-pricing anomalies, Chou *et al.* (2012) show that industry-related fundamentals command significant risk premiums that cannot be explained by stock-level risk factors like size, book-to-market

(BM) ratio and momentum. They also find that these well-known asset-pricing anomalies relate to industry classifications, further supporting the predictive value of industry fundamentals for stock market movements and economic fundamentals. In a recent study, however, Tse (2015) presents evidence to the contrary and shows that only one to seven industries have significant predictive power over stock market returns while some evidence of opposite predictive direction from the stock market to industries is also documented. Against this backdrop, this study utilises a recently developed non-linear causality test to explore the role of industrial electricity usage as a predictor of stock returns from a novel context and enlarges our understanding of stock market predictability. The analysis also contributes to the discussion on the predictive power of financial versus macroeconomic variables in stock market forecasting (e.g. Cochrane, 2008; Lettau and Ludvigson, 2009).

3. Methodology

Unlike other studies in the literature that are based on predictive regressions and GARCH-type models, we employ the recently developed *k*-th order non-parametric causality test of Nishiyama *et al.* (2011). This test is developed to incorporate higher order interrelationships inherently based on a non-linear dependence structure between the investigated variables in question, i.e. between industry returns, volatility and electricity usage.[1] Accounting for possible non-linearity to study causal relationships is particularly important in the context of this paper, which is a weakness in predictive models that are based on linear specifications. Considering the suggestion by Da *et al.* (2017) that the predictive value of industrial electricity usage is driven by its informational content relevant to capacity utilisation that allows to relate productivity shocks to business cycles, one can argue that the relationship between industrial electricity usage and stock market returns exhibits a non-linear (or state-dependent) pattern that serves as the basis for a countercyclical premium. Therefore, compared to standard causality tests and linear predictive models, the non-linear approach adopted in this study is more likely to be robust to misspecification errors. We next provide a brief description of the non-linear causality model proposed by Nishiyama *et al.* (2011), with the test restricted to the case when the examined series follow a stationary non-linear autoregressive process of order one under the null.

High-order non-parametric causality is motivated using the following non-linear dependence structure between the series

$$Y_t = g(y_{t-1}) + \sigma(x_{t-1})\epsilon_t \tag{1}$$

where $\{y_t\}$ and $\{x_t\}$ are stationary time series (i.e. industry return/realised volatility and, industrial electricity usage which is used as a predictor) and $g(.)$ and $\sigma(.)$ are unknown functions which satisfy certain conditions for stationarity. In general, x_{t-1} has information in predicting y_t^K for a given integer K. Consequently, the null hypothesis of non-causality in the Kth moment is described as

$$H_0 : E(y_t^K | y_{t-1}, \cdots, y_1, x_{t-1}, \cdots, x_1) = E(y_t^K | y_{t-1}, \cdots, y_1) \text{ w. p.1.} \tag{2}$$

where *w. p.* 1 is abbreviation for 'with probability one'. In formal terms, x_t is said not to cause y_t up to the Kth moment if

$$H_0 : E(y_t^K | y_{t-1}, \cdots, y_1, \; x_{t-1}, \cdots, y_1) = E(y_t^K | y_{t-1}, \cdots, y_1) \text{ w. p.1. for all } k = 1, \cdots, K \tag{3}$$

Note that in Equation 3, when $k = 1$, the null hypothesis reduces to non-causality in the mean. Following Nishiyama *et al.* (2011), we construct the test statistic $\hat{S}_t^{(k)}$ for each $k = 1, \ldots, K$ and implement the test for $k = 1$ to test for causality in the 1st moment (non-causality in mean), as well as for $k = 2$ in the 2nd moment (non-causality in variance).

4. Data and empirical findings

4.1. Data

The data on industry portfolios are obtained from Kenneth French's data library. Following Hong *et al.* (2007), we use monthly and daily returns for 38 value-weighted industry portfolios for the period January 1955 to December 2010. The sample period for industry data reflects the availability of the monthly industrial electricity usage data obtained from Zhi Da, which in turn are converted to their growth rates to ensure stationarity as in Da *et al.* (2017).[2] Six industries were dropped from the analysis due to missing observations; these industries are Agriculture, Garbage (sanitary services), Steam (steam supply), Water (irrigation systems), Government (public administration) and Other, leaving us with 32 industries in all. In addition to the industry portfolios, we extend causality tests to various alternative portfolios sorted on firm size and book-to-market ratio, also obtained from Ken French's website.

Figure 1 presents the monthly growth rates for industrial electricity usage as described in Da *et al.* (2017). Da *et al.* (2017) note that the correlation between the industrial electricity growth rate and the National Bureau of Economic Research (NBER) economic expansion indicator is 61%, while its correlation with investment growth is above 50%. Consistent with these reported correlations, we observe several notable spikes in Fig. 1 with a large drop observed following the recent global financial crisis in 2008. Since the industrial electricity usage data are available monthly, we compute the monthly realised volatility for the industry portfolios (as well as other alternative

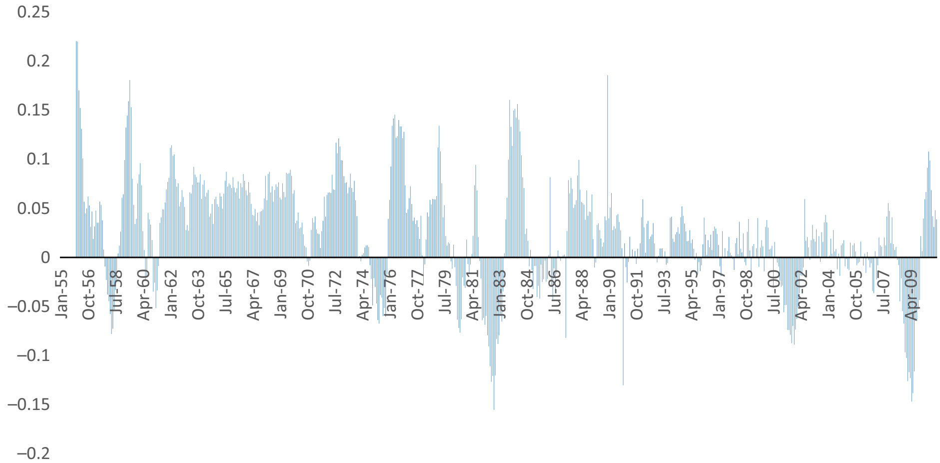

Figure 1 Industrial electricity usage growth. *Note.* The figure shows the monthly growth rates for industrial electricity usage, as described in Da *et al.* (2017), for the period January 1955–December 2010. [Colour figure can be viewed at wileyonlinelibrary.com]

portfolios sorts) using daily data. Realised volatility is computed as the sum of squared daily returns (see Andersen and Bollerslev, 1998)

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{4}$$

where $r_{\mathrm{t,i}}$ is the daily $M \times 1$ return vector and $i = 1, \ldots M$ the number of daily returns over a month.

4.2. Empirical findings

Table 1 presents the Nishiyama *et al.* (2011) non-parametric causality test statistics corresponding to the null hypothesis that industrial electricity usage growth does not cause industry return and realised volatility (RV).[3] The 5 per cent critical value of the test statistic is 14.38. In order to control for the effect of market and other risk factors in our tests, we examine raw industry returns as well as abnormal returns based on the single- and the three-factor models. We observe significant causality effects of industrial electricity usage on raw returns for 28 of 32 industries examined, consistent with the finding by Da *et al.* (2017) that industrial electricity usage contains predictive value for stock market returns. However, when industry returns are adjusted for the systematic risk proxies, we observe that causal effects become significantly stronger, particularly in the case of Chemicals, Electrical/Electronic Equipment, Food, Manufacturing, Financials, Communication, Services, Textiles, Utilities and Wholesale, suggesting that

Table 1 Non-linear causality tests for industry returns.

Industry	Raw returns		Market-adjusted returns		FF-adjusted returns	
	Mean	RV	Mean	RV	Mean	RV
Apparel	77.57*	22.21*	17.07*	1.091	33.90*	1.32
Cars—Transportation equip.	73.39*	15.55*	62.86*	5.247	7.06	5.55
Chair—Furniture and fixtures	14.69*	12.30	52.45*	2.824	66.64*	1.05
Chemicals	17.21*	46.34*	144.57*	26.81*	179.73*	27.12*
Construction	41.22*	23.48*	89.05*	2.12	15.52*	3.24
Electrical and electronic equip.	23.41*	35.64*	111.19*	6.92	93.40*	7.31
Food	62.88*	35.73*	99.62*	25.02*	117.33*	25.48*
Glass—Stone, clay and glass	2.42	18.36*	65.84*	7.81	106.55*	8.99
Instruments	51.69*	15.55*	64.50*	10.95	24.62*	13.38
Leather	104.44*	36.82*	32.42*	1.547	108.67*	1.57
Machinery	44.80*	25.05*	79.83*	6.847	124.99*	10.03
Manufacturing industries	27.88*	28.24*	128.56*	2.13	133.65*	0.68
Metal industries	110.40*	15.97*	74.23*	5.93	65.99*	8.12
Mines	23.32*	44.27*	17.07*	2.81	76.73*	3.41
Money—Financials	48.66*	11.87	158.16*	21.49*	132.65*	28.88*
Metal products	64.59*	25.05*	85.62*	13.53	88.54*	14.52*
Oil and gas extraction	17.02*	54.68*	12.36	1.33	34.39*	2.47
Paper	91.98*	39.04*	53.30*	6.09	167.64*	5.32
Phone	61.46*	38.87*	144.68*	0.50	140.45*	4.40
Printing and publishing	25.71*	39.04*	90.95*	8.69	134.36*	12.21
Petroleum and coal products	131.93*	77.02*	75.00*	3.81	48.06*	4.96
Retail stores	45.89*	56.95*	58.84*	17.62*	80.06*	17.48*
Rubber	109.55*	15.85*	103.95*	11.68	63.70*	19.80*
Smoke—Tobacco products	77.40*	35.06*	76.53*	0.16	39.03*	1.45
Services	65.86*	48.83*	132.94*	22.33*	164.22*	32.31*
Stone—Non-metallic minerals	69.44*	41.86*	27.78*	0.15	30.24*	0.06
Transportation	27.22*	24.68*	76.20*	12.17	5.52	19.01*
TV—Broadcasting	3.27	22.50*	90.36*	2.01	72.92*	1.26
Textile mill products	22.99*	14.26	119.22*	4.10	100.31*	3.64
Utilities	40.64*	31.57*	128.65*	22.72*	81.48*	22.87*
Wholesale	2.22	32.10*	95.42*	13.08	11.05	17.10*

Table 1 *Continued*

Industry	Raw returns		Market-adjusted returns		FF-adjusted returns	
	Mean	RV	Mean	RV	Mean	RV
Wood—Lumber and wood	3.92	25.00*	6.07	1.17	47.62*	1.67
Market return	65.86*	0.11				

The table presents the test statistics corresponding to the null hypothesis that industrial electricity usage growth does not cause industry return and realised volatility (RV). RV is the sum of squared daily returns for each month per Andersen and Bollerslev (1998). Following Hong *et al.* (2007), we use monthly and daily returns for 38 value-weighted industry portfolios for the period January 1955 to December 2010. Six industries were dropped from the analysis due to missing observations; leaving us with 32 industries in all. Market- and FF-adjusted returns are abnormal returns obtained using the single- and the three-factor models respectively.
*Significance at 5 per cent level (critical value is 14.38).

industry-specific factors may play out a role in the predictive ability of industrial electricity usage on stock returns.

The possible "industry effect" is further supported when the analysis is extended to causality on realised volatility. When we perform the test on the realised volatility of market returns, we see that industrial electricity usage fails to predict realised volatility at the aggregate market return level indicated by the test statistic of 0.11 in Table 1 for the market return. Interestingly, however, significant causal effects are found on realised volatility at the industry level, implied by significant test statistics for RV across all industries. Furthermore, when we examine adjusted industry returns after controlling for systematic risk factors, we see that causal effects on volatility become limited to only a handful of industries including Chemicals, Food, Financials, Retail, Services, and Utilities. These findings suggest that (i) the predictive ability of industrial electricity usage for the stock market is driven by an 'industry effect' that becomes evident when industry returns are adjusted for systematic risk factors; and (ii) this 'industry effect' is transmitted via the volatility channel, implying the ability of particular industries to serve as risk proxies that may provide information regarding future economic fundamentals.

Examining our findings in the light of the evidence by Da *et al.* (2017) that industrial electricity usage tracks the output of the very cyclical industries, we observe that the industries for which causality is found to be particularly strong are not all capital-intensive industries. However, this is a critical issue for industrial electricity usage to be advocated as a business cycle variable as cyclicality in output growth rates, as Da *et al.* (2017) argues, allows us to relate this variable to the business cycle. In order to provide more insight to this puzzle and further explore whether industrial electricity usage can

Table 2 Non-linear causality tests for alternative portfolio sorts

	Mean	RV
Small caps	42.41*	15.23*
Large cap	62.36*	26.81*
Growth	15.47*	34.37*
Value	35.10*	23.02*
Small growth	25.27*	13.10
Small value	8.36	17.13*
Big growth	23.18*	33.44*
Big value	83.11*	28.98*

The table presents the test statistics corresponding to the null hypothesis that industrial electricity usage growth does not cause return and realised volatility in portfolios sorted on firm size and book-to-market ratio. Monthly returns for portfolios on alternative sorts are obtained from Ken French's data library.

*Significance at 5 per cent level (critical value is 14.38).

serve as a business cycle variable, we extend the causality tests to alternative portfolios sorted on firm size and book-to-market ratio. The findings are presented in **Table 2**.

Interestingly, we see that the predictive ability of industrial electricity usage is primarily driven by big firms with high book-to-market ratios, indicated by large test statistics obtained for these portfolios. This finding becomes meaningful given the recent evidence by Wu and Mazouz (2016) that a contrarian industry portfolio strategy that exploits industry reversals tends to be heavily weighted in big firms and value stocks. Wu and Mazouz (2016) argue that large firms are the main contributors to industry performance and value stocks would come from losing industries with high book-to-market values. If industry reversals are primarily driven by big firms and value stocks in those industries, one can then argue that the countercyclical premium associated with industrial electricity usage growth is primarily driven by the industry components that drive stock reversals, thus resulting in the negative relationship between today's industrial electricity usage and stock returns in the future. This, in turn, provides further support to our previous argument that an 'industry effect' may be at play, driving the predictive ability of industrial electricity usage on future stock market returns.

5. Discussion

Our findings overall suggest that the predictive ability of industrial electricity usage may be primarily driven by an 'industry effect' that drives return reversals in the stock market and the finding that industrial electricity usage serves as a business cycle variable may simply be an artefact of return reversals driven by past industry performance. This is in line with the notion that the returns on industry portfolios are informative about macroeconomic fundamentals and suggest that the informational value of industrial electricity usage as a business cycle variable may simply be an artefact of long-term industry return reversals driven by industry fundamentals rather than industrial electricity usage serving as a proxy for capacity utilisation that links stock market returns to the business cycle. An important investment implication of this finding then is that a contrarian investment strategy involving those industries that serve as the basis for the "industry effect" driving the predictive ability of industrial electricity usage can be utilised to capture the countercyclical risk premium documented by Da *et al.* (2017). Consequently, it can be argued that industry effects that drive long-term return reversals can not only be utilised in market timing strategies but also must be taken into account when evaluating the predictive value of financial or macroeconomic variables for stock market returns.

The finding that the predictive ability of industrial electricity usage is largely driven by big firms with high book-to-market ratios also has implications regarding the documented risk premium associated with industrial electricity usage growth. Considering the recent finding by Wu and Mazouz (2016) that a contrarian industry portfolio strategy that exploits industry reversals tends to be heavily weighted in big firms and value stocks, one can argue that the countercyclical premium associated with industrial electricity usage growth may be driven by the industry components that drive stock reversals, thus resulting in the negative relationship between today's industrial electricity usage and stock returns in the future. Overall, these findings are in line with the notion that industries lead the stock market and possible industry effects must be accounted for when evaluating the predictive value of financial or macroeconomic variables for future stock returns. An important investment implication, however, is that a contrarian investment strategy involving the industries that serve as the basis for the 'industry effect' can be utilised to capture the countercyclical premium documented by Da *et al.* (2017).

6. Conclusion

This paper builds on the recent finding by Da *et al.* (2017) that industrial electricity usage growth rate carries predictive ability over stock returns by examining whether the predictive performance of this variable is primarily driven by particular industries leading the stock market. Using the non-parametric causality test by Nishiyama *et al.* (2011), we show that the predictive power of industrial electricity usage can be explained by an 'industry effect' which becomes evident when industry returns are adjusted for systematic risk factors. We observe that the 'industry effect' is primarily driven by a handful of industries including Chemicals, Food, Financials, Retail, Services, and Utilities and is transmitted via the volatility channel captured by the realised volatility of industry returns. We also show that the predictive ability of industrial electricity usage is largely driven by big firms with high book-to-market ratios. The findings are in line with the notion that the returns on industry portfolios are informative about macroeconomic fundamentals and suggest that the informational value of industrial electricity usage as a business cycle variable may be an artefact of return reversals driven by past industry performance. As part of future research, it would be interesting to revisit our results based on other non-parametric singular spectrum analysis- and frequency-based causality tests as employed in Hassani *et al.* (2016).

Notes

1. Given that the industrial electricity usage data are available in monthly frequency, we capture industry return volatility via the realised volatility estimator per Andersen and Bollerslev (1998).
2. We thank Kenneth French for making the industry data available on his website. Our thanks also go to Zhi Da for graciously providing the data for industrial electricity usage.
3. As indicated earlier, the Nishiyama *et al.* (2011) test allows us to detect for causality at higher moments, which in our case is squared returns, capturing volatility. Given that the evidence in favour of predictability for squared returns is weak (restricted to only five cases: food under market- and FF-adjusted returns, leather under FF-adjusted returns, mines under raw and FF-adjusted returns, oil and gas extraction under FF-adjusted returns, and paper under market-adjusted returns), we have reported the results in **Tables A1** and **A2** in the Appendix, and relied more on results for realised volatility as the appropriate measure of volatility.

References

Andersen, T.G. and Bollerslev, T., 1998. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39, 4, 885–905.

Ang, A. and Bekaert, G., 2007. Return predictability: is it there? *Review of Financial Studies* 20, 651–707.

Boudoukh, J., Richardson, M.P. and Whitelaw, R.F., 2008. The myth of long-horizon predictability. *Review of Financial Studies* 21, 1577–1605.

Chou, P.-H., Ho, P-H. and Ko, K.-C., 2012. Do industries matter in explaining stock returns and asset-pricing anomalies? *Journal of Banking & Finance* 36, 355–370.

Cochrane, J.H., 2008. The dog that did not bark: a defense of return predictability. *Review of Financial Studies* 21, 1533–1575.

Da, Z., Engelberg, J. and Gao, P., 2015. The sum of All FEARS investor sentiment and asset prices. *Review of Financial Studies* 28, 1, 1–32.

Da, Z., Huang, D. and Yun, H. 2017. Industrial electricity usage and stock returns. *Journal of Financial and Quantitative Analysis*, 52, 1, 37–69.

Welch, I. and Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21, 1455–1508.

Hassani, H., Huang, X., Gupta, R. and Ghodsi, M., 2016. Does sunspot numbers cause global temperatures? A reconsideration using a non-parametric causality test. *Physica A: Statistical Mechanics and its Applications* 460, 1, 54–65.

Hong, H., Torous, W. and Valkanov, R., 2007. Do industries lead stock markets? *Journal of Financial Economics* 83, 367–396.

Huang, D., Jiang, F., Tu, J. and Zhou, G., 2015. Investor sentiment aligned: a powerful predictor of stock returns. *Review of Financial Studies* 28, 791–837.

Jiang, H. and Sun, Z., 2014. Dispersion in beliefs among active mutual funds and the cross-section of stock returns. *Journal of Financial Economics* 114, 2014, 341–365.

Lettau, M and Ludvigson, S, 2009. Euler equation errors. *Review of Economic Dynamics* 12, 255–283.

Nishiyama, Y., Hitomi, K., Kawasaki, Y. and Jeong, K., 2011. A consistent nonparametric test for nonlinear causality: specification in time series regression. *Journal of Econometrics* 165, 1, 112–127.

Rapach, D. and Zhou, G. 2013. Forecasting stock returns. In *Handbook of Economic Forecasting*, volume 2. Elsevier, pp. 328–383.

Rapach, D.E., Ringgenberg, M.C. and Zhou, G., 2016. Short interest and aggregate stock returns. *Journal of Financial Economics* 121, 46–65.

Tse, Y., 2015. Do industries lead stock markets? A reexamination. *Journal of Empirical Finance* 34, 2015, 195–203.

Wu, Y. and Mazouz, K., 2016. Long-term industry reversals. *Journal of Banking & Finance* 68, 236–250.

Appendix

Table A1 Non-linear causality tests for squared industry returns

Industry	Squared raw returns	Squared market-adjusted returns	Squared FF-adjusted returns
Apparel	5.56	7.57	5.47
Cars—Transportation equip.	8.40	5.82	11.59
Chair—Furniture and fixtures	8.14	14.29	8.59
Chemicals	2.83	6.27	12.78
Construction	6.00	8.47	19.68
Electrical and electronic equip.	6.40	7.62	7.89
Food	8.67	21.20*	18.85*
Glass—Stone, clay and glass	7.47	10.13	10.88
Instruments	4.86	8.75	7.47
Leather	7.81	14.08	14.83*

Table A1 *Continued*

Industry	Squared raw returns	Squared market-adjusted returns	Squared FF-adjusted returns
Machinery	8.60	2.98	2.54
Manufacturing industries	2.00	5.32	10.15
Metal industries	5.60	12.50	12.58
Mines	16.26*	7.57	27.20*
Money—Financials	6.85	8.73	6.65
Metal products	2.50	4.68	5.09
Oil and gas extraction	5.05	14.19	18.50*
Paper	2.74	17.66*	10.11
Phone	4.60	7.30	13.27
Printing and publishing	5.26	4.15	2.06
Petroleum and coal products	3.88	3.69	10.03
Retail stores	4.53	9.29	8.71
Rubber	4.21	3.02	3.47
Smoke—Tobacco products	6.85	11.73	13.86
Services	4.98	4.67	4.26
Stone—Non-metallic minerals	6.74	4.26	4.85
Transportation	4.80	3.90	4.31
TV—Broadcasting	5.75	3.38	4.59
Textile mill products	5.37	8.52	12.47
Utilities	4.15	9.25	9.11
Wholesale	4.83	6.69	7.14
Wood—Lumber and wood	2.98	5.37	3.68
Market return	4.98		

The table presents the test statistics corresponding to the null hypothesis that industrial electricity usage growth does not cause industry squared return. Following Hong *et al.* (2007), we use monthly and daily returns for 38 value-weighted industry portfolios for the period January 1955 to December 2010. Six industries were dropped from the analysis due to missing observations; leaving us with 32 industries in all. Market- and FF-adjusted returns are abnormal returns obtained using the single- and the three-factor models respectively.

*Significance at 5 per cent level (critical value is 14.38).

Table A2 Non-linear causality tests for alternative portfolio sorts

	Squared Return
Small caps	7.81
Large cap	2.86
Growth	2.76
Value	6.15
Small growth	8.09
Small value	11.40
Big growth	3.21
Big value	3.83

The table presents the test statistics corresponding to the null hypothesis that industrial electricity usage growth does not cause squared return in portfolios sorted on firm size and book-to-market ratio. Monthly returns for portfolios on alternative sorts are obtained from Ken French's data library.

*Significance at 5 per cent level (critical value is 14.38).