ELECTRICITY USAGE AND ASSET PRICING OVER THE BUSINESS CYCLE

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Submitted for the Degree of Doctor of Philosophy in Economics

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Scientific-disciplinary sector: SECS-S/03

Universities of Florence, Pisa, and Siena Joint PhD Program in Economics

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Cycle XXXIV - Academic Year: 2021-2022

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Introduction:

The existence of a linkage between financial markets and business cycles has long been known. The stock market tends to be a leading indicator of the business cycle since investors look to a plurality of indicators and tend to exit the market at or before an economic contraction and return to the market during recovery. Nevertheless, there exists a gap between the asset pricing literature and the business cycle literature in predicting stock returns, which is a crucial issue for investors, portfolio, and risk managers.

Still, the correlation between stock returns and business cycle variables was recognized by different theories and models (e.g. by the real business cycle theory (RBC) (Kydland & Prescott, 1982; Plosser and Long, 1983), the consumption-based asset pricing model (Rubinstein, 1976; Breeden-Litzenberger, 1978; Breeden, 1979; Lucas, 1978 and later Campbell & Cochrane, 1999 among others), the production-based asset pricing model (Brock, 1982; Cox, Ingersoll, and Ross, 1985; Berk, Green and Naik, 1999; Cochrane, 1991; Restoy and Rockinger, 1994,et al.)).

Out of these models, the consumption-based models presented some issues such as, for example, poor measurement and hence the uselessness of the consumption Euler equation, which is why the consumption processes used in general equilibrium models did not reflect the empirically observed consumption. Besides, the consumption was not a good proxy for economic activity. The empirical performance of consumption-based approach did not manage to explain the relationship between financial variables and the business cycle. Therefore, production-based models, mostly inspired by RBC models, were proposed to be predictor models of relation between economic fluctuations and expected stock returns because they presented a direct connection between asset returns and production variables that indicate changes in economic activity, instead of making use of relatively smooth consumption series.

Price-based financial variables (like E/P, dividend yield, book-to-market, size, the latter two being the variables of the Fama-French model (Fama & French 1993, 1996), the most used modern model in stock returns analysis) have long been considered the only variables capable of explaining the stock returns well (Campbell, 2003; Cochrane, 2008; Lettau and Ludvigson, 2009; Lewellen, 2004 among others) due to their linkage to expected returns through price and the capability of predicting returns as long as they capture information about the risk premium.

In 2017 Da, Huang & Yun have published an article “Industrial Electricity Usage and Stock Returns” where they have stressed the fact that stock market returns depended on business cycle and proposed a macroeconomic variable with superior properties in explaining stock returns, the industrial electricity usage growth rate. This variable has a pervasive link to production process (industrial electricity usage is linked to investment and to capacity utilisation because, in case of investment, it increases if the production machinery is being enlarged and, in case of capacity utilisation, it should increase if the same machinery is being utilized more intensively). Most industrial production activities involve the use of electricity which cannot be stored and therefore, it must be necessarily employed in the production process, otherwise, it will be wasted. Consequently, the industrial electricity tracks production and output in real time. This idea is not new, as it was pioneered in Italy by Bodo & Signorini (1987) and Bodo, Cividini & Signorini (1991) who managed to forecast the Industrial Production Index in real time using monthly and infra-monthly electricity consumption data ahead of the release of the official statistic by the Italian National Statistical Institute (Istat, *Istituto Nazionale di Statistica)*.

Zhi Da et al. (2017) show that industrial energy usage performs optimally in the prediction of US stock returns. However, despite the previous encouraging results, a deeper understanding of the industrial technologies used in the production process suggests that the matter is not so simple. The reason for this can be found in the concept of energy efficiency of the equipment that firms use. A comparable measure of energy efficiency is the intensity of energy consumption which is the ratio of the total final energy consumption (in GJ) and the value added at constant price. Another possible efficiency measure is the specific energy consumption per unit of the product. Moreover, the energy efficiency is closely linked to the analysis of the carbon footprint (emissions of greenhouse gases (GHG)) that each firm leaves during its production process, with special attention paid to the emissions of CO2.

So, after applying the Fama & French three-factor model on the Italian stock market, the main task of this work is to check whether the industrial electricity usage variable can predict future Italian stock returns alone and after the correction using one of energy efficiency measures, and eventually one or two “boosters” of energy efficiency improvement (forward energy price change and carbon permits’ price change).

The theoretical basis can be found in a production-based model which uses a production technology input variable that changes throughout time like, for example, in Burnside, Eichenbaum, Rebelo (1995) (BER 95) where the authors present the theory of direct correlation between procyclical capital utilisation rates and cyclical changes in labour productivity for different degrees of returns to scale. In their study the growth in capital utilisation is approximated by industrial electricity usage and capital workweek (the authors make a direct comparison to the empirical finding of the real business cycle models). In two specifications out of three presented by these authors, the technology is state-dependent. Moreover, the first specification of the relation between capital services and electricity usage is by way of Leontief technology. So, only a weak substitutability between factors holds, which is one of the main characteristics of the energy input. The lack of substitutability of the energy input becomes apparent if the physical constraints on the production process are correctly modelled (e.g. Roma and Pirino (2009)). However, simply relying on a fixed-coefficients production process to model the lack of substitutability does not capture the irreversible degradation associated with the use of the energy input, entropy, which is the fundamental source of negative externalities including GHC. This work modifies the fixed-coefficient energy-production relationship proposed by BER 95 to 1) let it vary throughout the sample period based on available energy intensity measures, and 2) associate GHC production with the level of energy utilisation.

The model is applied to three energy-intensive Italian industrial sectors, Construction & Materials, Chemicals and Basic Resources and attempts to predict the return of a portfolio containing the stock belonging to each sector listed on the Italian stock exchange. The monthly time-series of the listed stock prices were downloaded from the website www.investing.com, the monthly time-series of the electricity consumption of the subsectors of Cement, Chemicals, Steel and Non-ferrous metals were kindly provided by Terna s.p.a., which is the supplier of the detailed statistics regarding the electricity demand and supply monthly and in real time (the data is being updated every 15 min) based on the forecasts and actual data coming from MSD market. All energy-efficiency measures were downloaded from Odyssee Mure online database. The same procedure is applied to the Swedish data. The only difference is that here the data relative to the industrial electricity consumption come from the Statistics Sweden and there is no subdivision in Steel and Non-ferrous Metals of the Basic Resources electricity consumption time-series. The rest of the data come from the same sources as for Italy.

As for the econometrics of this research, the OLS (ordinary least squares) procedure is used to find out the reliability of the prediction variables. Being affected by the seasonality, the energy consumption monthly series are seasonally adjusted by means of the TRAMO-SEATS procedure of Demetra+ software. The energy efficiency measures being available only at annual level, the Denton procedure is used to produce monthly series by adapting the low-frequency values to the fluctuations in energy price (PUN for Italy, variable energy price for Sweden) available at higher frequency. The monthly time-series of energy price acts like the indicator series which is highly correlated with the available data series.

The plan of the thesis is as follows: Chapter 1 contains my paper on the application of the Fama-French asset pricing model with financial variables to the Italian stock market; Chapter 2 deals with the energy input and entropy in the production function and uses both in an ad-hoc asset pricing model applied to the Italian stock returns, the structure of the chapter is as follows: Section 2.1. presents the review of previous literature, which is relevant for this research and explains in detail the underlying model, Section 2.2. describes the data and the methodology used, Section 2.3. tests the models with financial variables, Section 2.4. presents the empirical results relative to the application of the elaborated model, Section 2.5. combines the results of the previous two sections and tests the augmented models with financial variables; Chapter 3 enriches the study by performing the previous tests in a reduced form on the Swedish data and concludes.

CHAPTER 1. Performance of Value- and Size-based Strategies in the Italian Stock Market

The stock returns on the Italian Stock Market, characterised by a large number of small listed companies, are problematic to predict if the investors and portfolio managers use the standard Capital Asset Pricing Model which until not long ago was the most widely used asset pricing model. A valid alternative (Fama and French, 1993) that was successful in predicting US Stock returns, is tested on the Italian data in this chapter (Pirogova & Roma, 2020).

In particular, it investigates the performance of size- and value-based strategies in the Italian Stock Market in the period 2000 - 2018. Previous research (Beltratti and Di Tria (2002)) argued the impossibility to define properly value-sorted portfolios due to the inaccuracy of book-to-market ratios available for Italian listed stocks. Using more accurate data, we implement portfolios sorting based on value and growth stocks, in order to assess the relevance of the value factor in the Italian Stock Market. We find that the CAPM fails to explain the cross section of returns on the different strategies while the Fama and French (1993) three-factor model provides a better fit. The results show that all three factors are significant in explaining Italian stock returns during the sample period. Unlike previous studies, which either found no value effect at all (Barontini (1997); Aleati et al., (2000)) or no clear-cut results when testing the book-to-market variable (Bruni et al. (2006); Rossi (2012)), we find that the value factor is statistically significant, and the associated risk premium is of a considerable size.

1.1. Introduction

The Capital Asset Pricing Model (CAPM) postulates a linear dependency of expected stock returns on their regression coefficient on the market factor. A number of theoretical and empirical inconsistencies of the CAPM model are known, namely the critiques by Roll (1977) and Hansen and Richard (1987) on the testability of the model, and empirical inconsistencies like the small-firm effect by Banz (1981) and the inability to explain returns of value- and growth-sorted portfolios by Fama and French (1993). Such issues have motivated extensive research into alternative models.

In response to the empirical shortcomings, Fama and French (1993) proposed a three-factor model in which additional common sources of variation in stock prices are represented by the difference in return of high book-to-market stocks and low book-to-market stocks (HML), and the difference in return of small and big stocks (SMB). The Fama French (1993) (henceforth FF) model has been very successful in explaining stock returns compared to multifactor models based on macroeconomic variables in the US. Fama and French (1998) extended their results to other major stock markets.

The economic mechanism underlying the pricing impact of the additional FF factors is not however completely understood, and it is often interpreted as an example of Ross (1976) Arbitrage Pricing Theory.

While there is extensive empirical evidence of the performance of the FF model in the US and other major stock markets like the UK and Japan, few papers have investigated it on the Italian stock market. There have been contributions by Barontini (1997), Cavaliere and Costa (1999), Aleati et al. (2000), Beltratti and Di Tria (2002), Alesii (2006), Brighi and D'Addona (2008), and Silvestri and Veltri (2011) who test different multifactor model specification including FF factors. Bruni et al. (2006) and Rossi (2012) stick to the FF testing framework and concentrate on SMB and HML.

In general, there was high heterogeneity across all the studies on the Italian Stock Market as far as the sample period, model and econometric method were concerned. The sample period range in these studies was very wide, from 9 years (Cavaliere and Costa (1999)) to 86 years (Alesii (2006)), which led to a different number of observations and consequently different methods of conducting the tests.

As for the FF risk factors, previous results broadly support the conclusion that market beta and the size factor are needed to explain the variations in Italian stock returns, whereas the book-to-market (B/M) ratio was significant in some studies and not significant in others.

Aleati et al. (2000), who studied the sample period 1981-1993, were concerned with the explanatory power of HML and SMB for average stock returns compared to the Chen, Roll and Ross (1986) macroeconomic factors. Applying different econometric methods, they failed to detect a significant role of the HML factor on its own. They applied tests on single stock returns rather than portfolios because of the small number of stocks available. Beltratti and Di Tria (2002) considered the sample period 1990-2000 and used FF and macroeconomic factors to explain the returns of portfolios sorted by industry, size, and dividend yield. They claimed that the poor quality of book-to-market data for Italian stocks prevented reliable calculation of the HML factor which they substituted with dividend yield. They found contradicting results for the explanatory power of the FF model in cross-sectional as opposed to time-series regressions.

Bruni et al. (2006) and Rossi (2012) carried out time series tests on size and value-sorted portfolios in the 1989-2004 sample period and concluded in favor of the FF three-factor specification, including the HML value-growth factor, against the CAPM, for the explanation of the return on value- and size-based portfolios, although the significance of HML was not clear cut.

In this paper we follow the approach of Cavaliere and Costa (1999), Bruni et al. (2006) and Rossi (2012), comparing the FF model with the CAPM in the pricing of size- and value-based strategies. We extend the testing period to the most recent sample 2000-2018, which includes the financial crises of 2002, 2005 and 2007-2008, with an overall negative stock index return of -48%. Moreover, we address a number of shortcomings of the tests of the FF model in the Italian Stock Market used in previous studies. We show that B/M data in Datastream, the data source used in many previous studies (Beltratti and Di Tria (2002), Bruni el al. (2006) and Rossi (2012) among others) is often inaccurate. We use accurate sources for market capitalization and book-to-market data in order to correctly define the SMB and especially the HML factor. We also overcome the incompleteness of the universe of stocks used by Bruni et al. (2006) and Rossi (2012) who tested an arbitrary small sample of 109 ordinary stocks that were listed in the period 1989-2004, excluding savings and preferred stocks[1], representing only about 50 percent of the market capitalization[2].

Our empirical contribution is to identify more accurate data sources and show that a properly defined HML factor is a statistically significant explanatory variable for the return of value- and size-sorted portfolios of Italian stocks. Consistent with international evidence, these returns cannot be explained by the CAPM. Moreover, the risk premium on the HML factor in our sample is about 5% on a yearly basis and is statistically significant.

The plan of the paper is as follows: in Section 2 we describe the data and the problems detected with often-used B/M and market capitalization data, which we check against reliable sources. We deal with the construction of the sorted portfolios and FF factors based on our more accurate data. Section 3 contains statistics on the sorted portfolio returns. In Section 4 we apply a single factor model and the FF model to the returns of the size- and value-sorted portfolios and show that the additional HML and SMB factors are essential explanatory variables for these strategies. We also analyze the key components of HML factor return. Section 5 concludes.

1.2. Data and Research Methodology

We use all the stocks traded in the period between the end of June 2000 and the end of June 2018. The cumulative sum of stocks used in our variable sample, considering listed stocks and new listings, is 499. These stocks had a positive volume at some time in the sample period. The available stocks were grouped into portfolios according to size-based and value-based strategies by sorting stocks in ascending order, first according to market capitalization at the end of June each year, and then

[1] FF (1993) noted that the assignment of book value to preferred stocks requires specific assumptions.

[2] Using the same source, we could not exactly replicate their results. It was not possible to get the exact data used by the authors due to the fact that some companies have merged with others and Datastream (and Bloomberg) merged their relative values, book-to-market and prices.

according to book-to-market at the end of the previous year. We considered a variable sample that takes into account new listings and delistings. In order to be included in a portfolio, a stock must be traded at the end of June and at the end of the previous year. We used adjusted month end prices to compute monthly returns for each stock over the sample period, and if a monthly return was missing the stock was excluded from the portfolio in that month. This narrows the sample. The number of stocks listed and processed in each year of our sample period ranges between 224 and 301. Hence, we decided to follow Bruni et al. (2006) and Rossi (2012) and sorted stocks into 16 portfolios instead of 25 as in FF.

We took special care in addressing the quality of the data. As already mentioned, because of the "poor quality of the data regarding the book-to-market", Beltratti and Di Tria (2002) gave up the HML factor and chose the dividend yield as a proxy. We obtained adjusted stock returns, book-to-market and market capitalization data from Datastream. We also obtained end-of-June market capitalization data directly from the Italian Stock Exchange (Borsa Italiana), and book-to-market data from the publication *Indici e Dati* by Mediobanca S.p.A. (Mediobanca), which contains carefully processed data and is considered an authoritative source for Italian listed-stock statistics. We also used stock price data from Bloomberg to counter check anomalous returns which we corrected in few cases. Our market excess return is computed using FTSE Mib and 3-month Euribor.

We considered whether the book-to-market and market capitalization data available in the Datastream database can be reliably used in the sorting procedure. The B/M value is based on the book value attributed to each stock, compared to its market value. The book value is obtained from company financial statements at the end of each calendar year, i.e. 31st December, and used in the sorting at the end of June of the following year, when this information is certainly in the public domain. When a company has different categories of stocks other than common stock outstanding, the attribution of book value to the different categories depends on the seniority of stockholders in case of liquidation. We investigated the reliability of B/M ratios for individual stocks by comparing the information available from Datastream and from *Indici e Dati* by Mediobanca.

We also checked whether market capitalization data available in Datastream is reliable by comparing it with data obtained directly from the stock exchange Borsa Italiana.

Table 1 contains summary statistics on the discrepancies of year-end B/M values in Datastream and Mediobanca for all available stocks, as well as discrepancies between 30th June market capitalization values in Datastream and those obtained from the Italian Stock Exchange (about 5000 observations for which we have both values). While small discrepancies may be due to rounding, B/M point values in Datastream are often substantially different from those published by Mediobanca, and at times even negative, providing some support for the argument that the Italian B/M ratios available in commercial databases are not reliable and need to be carefully considered before they are used. A lesser issue was detected for market capitalization values.

Table 1*: Frequency of large deviations between data sources*

	Book-to-Market		**Market Capitalization**	
	Datastream vs Mediobanca		**Datastream vs Borsa Italiana**	
Threshold value of deviation	No. of Deviations	Freq.cy	No. of Deviations	Freq.cy
2%	1395	27.5%	259	4.8%
5%	847	17.2%	104	1.9%
10%	535	10.8%	89	1.6%
15%	372	7.5%	78	1.4%

Note: The deviations are calculated as the percentage difference of the Datastream value from the Mediobanca value for Book-to-Market data on 31 December and as the percentage difference of the Datastream value from the Borsa Italiana value for the market capitalization on June 30, when both values are available. Observations that exceed the thresholds are reported.

In the FF framework B/M and market capitalization values can be used to devise specific trading strategies through sorted portfolios, and also to derive more general factors that can explain the expected return of specific strategies, namely the HML and SMB. It is important that the quantiles into which stocks are sorted are computed according to accurate B/M and market capitalization data. Wrong values for market capitalization and book-to-market alter the break points for the computation of quantiles and modify the composition of sorted portfolios[3].

We sorted stocks into quartiles according to June market capitalizations from Borsa Italiana and year-end B/M from Mediobanca, which we consider to be more reliable. Table 2 describes the average of the quartiles into which stocks are binned by market capitalization and B/M value in order to simulate strategies based on value and size. High B/M indicates value stocks that the stock market undervalues with respect to their equity. The sorting procedure produces one such table defining 16 portfolios at the end of June, when portfolios are rebalanced, for every year between 2000 and 2018, and here only the average of the break points are reported. As is well known, small stocks in Italy can be really small, with market capitalizations as low as 0.3 million euro. High B/M values are, on

[3] A problem with the Datastream data is also the tendency to report the previous period market capitalization and B/M even after a stock is no longer listed. If not identified, this issue increases the number of stock processed every year in sorting by size and B/M, altering the definition of quantiles and the composition of value and size portfolios. As returns for stocks which are no longer listed are not available, the portfolios shrink in size when their returns are computed, and contain the wrong stocks, making it difficult to attribute returns to value and size categories.

average, more pronounced for small stocks, with top (average) B/M values of about 5, which are twice as high as B/M values found for large stocks, about 2.5. Large stocks tend to have lower B/M. Over time (not reported), B/M tends to increase in our sample for stocks of all sizes, but small stocks in recent years have sometimes reached B/M values over 9. We labeled the 16 portfolios P1 through P16, characterized by size and value according to the structure described in Table 3.

The additional FF risk factors HML and SMB result from partitioning the same stocks into six portfolios by sorting according to market capitalization into two groups, small and big, and then sorting these two groups by B/M according to percentiles corresponding to 30, 40 and 30 percent into Growth, Neutral, and Value stocks. The additional factors are then defined as in FF.

1.3. Sorted Portfolios Returns

The monthly returns of each of the sixteen portfolios were calculated from the end of June of each year for the subsequent twelve months, starting with July. We computed equally weighted and value weighted returns. The calculation was repeated for each year to produce returns for the whole duration of the sample.

Table 2: *Average Size and B/M Quartiles*

Size (Million Euro)	**Growth ⟶ Value** B/M			
0.3 - 57	0.10-0.51	0.51 - 0.91	0.91-1.49	1.49-4.99
57-198	0.12-0.59	0.59 - 0.91	0.91-1.41	1.4-4.07
198-946	0.12-0.47	0.47 - 0.8	0.8-1.33	1.33-3.65
946-6,916	0.10-0.36	0.36 - 0.68	0.68-1.04	1.04-2.49

Note: The first column describes the average size of stocks grouped into quartiles in ascending order during the sample period June 2000 - June 2018. On the same row of the size bracket there are reported the average B/M values for each of the four quartiles into which a size group is subdivided.
Abbreviation: B/M, book-to-market ratio.

Table 4 shows descriptive statistics for the time series of equally weighted portfolio returns obtained by this procedure. With two exceptions (P5 and P6), the average return on the size-value strategies is positive. Returns on the first portfolio (P1) which contains the smallest stocks with the lowest B/M are the most erratic, as it can be seen from the wide range and descriptive statistics in Table 4.

Table 3: *Names of Size-/Value-sorted portfolios*

	Growth $\longrightarrow$ Value			
Small				
$\downarrow$	P1	P2	P3	P4
	P5	P6	P7	P8
	P9	P10	P11	P12
	P13	P14	P15	P16
Big				

There are signs of a size effect: when the size of the companies in the portfolios increases, there is a certain tendency in portfolio returns to decrease which means that the sample shows an inverse relationship between size and stock returns. The portfolios containing the larger stocks (P13-P16) earn a return somewhat lower than those containing the smaller stocks (P1-P4). If portfolios with different B/M ratio are considered, there are also signs of a value effect: as the ratio grows, the portfolio returns tend to grow, as the high B/M portfolios P4, P8, P12 and P16 show higher returns than the corresponding low B/M portfolios of the same size, namely P1, P5, P9 and P13. When we consider value weighted returns, Table 5 shows that the outliers in the return of small size portfolios are evened out and the small/growth portfolio P1 no longer has a positive return. As the B/M ratio of the portfolio grows, once again the average return tends to grow: P4, P8, P12 show higher returns than the corresponding low B/M portfolios of the same size: P1, P5, and P9, however the big/value portfolio P16 has about the same return as the big/growth portfolio P9.

Table 6 provides a similar analysis for the equally weighted and value weighted HML and SMB factors. These factors correspond to excess returns, and their average return represents the risk premium for a unit exposure to the factor. Differently from the case of macroeconomic factors (Mazzariello and Roma (1999), Panetta (2002)) no further estimation is needed.

Table 4: *Descriptive statistics of the equally weighted sorted portfolios returns*

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
Mean	.00434	.00108	.00565	.00932	-.00141	-.00046	.00013	.00436	.00168	.00466	.00425	.00383	.00051	.00175	.00201	.00113
Median	-.00819	-.00064	.00433	.00690	-.00091	.00472	.00239	.00496	.00564	.00924	.00434	.01029	.00595	.00687	.00712	.00110
Std. Deviation	.13089	.06607	.06780	.07178	.06954	.05643	.05874	.06447	.05926	.05856	.05722	.06789	.06418	.05300	.05679	.07441
Variance	.01713	.00437	.00460	.00515	.00484	.00318	.00345	.00416	.00351	.00343	.00327	.00461	.00412	.00281	.00322	.00554
Kurtosis	64.048	1.287	.631	1.722	1.588	.680	.588	1.174	1.878	1.848	.814	.350	1.741	1.422	1.012	.878
Skewness	6.479	.258	-.007	.733	.078	-.352	-.243	-.004	-.065	-.015	-.095	-.266	-.463	-.292	-.187	-.303
Minimum	-.18712	-.18349	-.20682	-.18700	-.22935	-.19197	-.17840	-.19115	-.20848	-.18686	-.17983	-.18620	-.23472	-.20844	-.17919	-.24015
Maximum	1.40947	.22345	.19059	.27394	.26847	.16902	.14623	.21639	.21434	.23286	.17887	.21314	.21030	.20709	.21715	.24767

Table 5: *Descriptive statistics of the value weighted sorted portfolios returns*

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
Average	-.00392	.00160	.00754	.01019	-.00116	.00150	-.00087	.00409	.00055	.00397	.00484	.00182	.00137	.00108	.00316	.00111
Median	-.01110	-.00129	.00639	-.00016	-.00272	.00595	.00184	.00459	.00596	.00759	.00799	.00397	.00719	.00791	.00954	.00258
Std. Deviation	.08239	.06745	.07508	.07998	.07003	.05736	.06267	.06613	.05900	.06171	.05761	.07055	.06417	.05698	.05506	.07598
Variance	.00679	.00455	.00564	.00640	.00490	.00329	.00393	.00437	.00348	.00381	.00332	.00498	.00412	.00325	.00303	.00577
Kurtosis	4.143	4.246	.809	4.119	1.439	.924	1.342	1.455	1.375	1.587	.865	.217	2.085	4.284	.475	1.075
Skewness	1.071	.825	.061	1.320	-.052	-.299	-.070	.010	-.120	.037	-.001	-.301	-.480	.205	-.273	-.369
Minimum	-.21100	-.16657	-.22980	-.18037	-.23995	-.20307	-.19775	-.21195	-.20480	-.19842	-.16409	-.20403	-.25788	-.22386	-.16531	-.25343
Maximum	.41971	.36843	.23303	.40955	.26399	.19901	.25183	.22872	.20586	.21668	.18692	.19503	.20449	.31482	.17303	.24785

From Table 6 the two risk premia for the equally weighted factors, λ_{HML} and λ_{SMB} are equal to 0.4% and 0.035%, respectively, on a monthly basis, or 4.8% and 0.42% annualized. The size of the value factor risk premium is considerable. On the other hand, the average of the stock market index excess return over the risk-free rate, λ_{MK}, was negative over the sample period and equal to -0.32%, or -3.8% annualized.

Table 6: *Descriptive statistics of the three risk factors*

	HML	SMB	HMLVW	SMBVW	Rm-Rf
Mean	0.00401	0.00035	0.00454	-0.00055	-0.00327
Median	.00456	-.00210	0.00463	-.00023	.00338
Standard Deviation	.03267	.02887	0.03093	.02419	.05962
Sample Variance	.00107	.00083	.00096	.00059	.00355
Kurtosis	24.267	14.196	.834	.982	.611
Skewness	-2.859	2.159	-.078	.268	-.247
Minimum	-.27569	-.06884	-.12638	-.06722	-.17010
Maximum	.08194	.21638	.09369	.09390	.20672
Count	216	216	216	216	216

Abbreviations: HML, high book-to-market stocks and low book-to-market stocks; SMB, small and big stocks.

Table 7 contains the correlation matrix of all equally weighted variables. We can see that the size factor SMB is correlated positively with the return of the smallest stocks portfolios (P1-P12), and the correlation decreases as size increases, with portfolios containing larger stocks (P13-P16) showing inverse correlations with the size factor, which is what we would intuitively expect. A pattern of correlation between the HML factor and portfolio returns is also evident, with the return of the value portfolios P4, P8, P12, and P16 positively correlated with this factor and P1, P5, P9 and P13 negatively correlated with it.

Table 7: *Correlation of portfolio returns and factors*

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	HML	SMB	Rm-Rf
P1	1.00																		
P2	.611	1.00																	
P3	.485	.767	1.00																
P4	.515	.782	.734	1.00															
P5	.487	.750	.703	.685	1.00														
P6	.461	.777	.763	.740	.830	1.00													
P7	.528	.808	.770	.775	.821	.836	1.00												
P8	.488	.793	.780	.758	.776	.830	.841	1.00											
P9	.465	.782	.724	.740	.866	.857	.824	.772	1.00										
P10	.482	.766	.726	.725	.810	.843	.821	.772	.837	1.00									
P11	.491	.752	.723	.704	.825	.821	.828	.825	.816	.865	1.00								
P12	.539	.769	.736	.735	.777	.801	.826	.822	.793	.830	.859	1.00							
P13	.405	.655	.606	.549	.769	.775	.694	.650	.799	.780	.749	.721	1.00						
P14	.428	.716	.669	.657	.795	.826	.762	.714	.818	.825	.842	.810	.853	1.00					
P15	.432	.756	.725	.705	.776	.822	.794	.791	.810	.843	.828	.856	.824	.889	1.00				
P16	.445	.701	.706	.675	.743	.763	.795	.757	.757	.807	.826	.877	.766	.839	.901	1.00			
HML	-.475	-.050	.135	.184	-.158	.003	.071	.214	-.106	.012	.080	.170	-.198	-.028	.113	.206	1.00		
SMB	.604	.370	.316	.376	.160	.148	.249	.282	.065	.010	.021	.038	-.181	-.135	-.095	-.120	-.247	1.00	
Rm-Rf	.408	.685	.665	.633	.770	.778	.758	.727	.779	.794	.793	.799	.858	.891	.907	.906	.044	-.152	1.00

Abbreviations: HML, high book-to-market stocks and low book-to-market stocks; SMB, small and big stocks.

The correlation between HML and SMB is low and equal to -0.247 showing that these factors capture different aspects of the sample of stock returns.

When value weighted factors are considered (Table 6) the risk premium of the size factor (SMBVW) becomes negative, and hence no size effect can be detected. On the other hand, the risk premium on the value weighted HML factor (HMLVW) remains highly positive, and it is larger (0.0045 on a monthly basis, 5.4% annualized, more than twice its standard deviation), indicating that big stocks rather than small stocks are the source of the value premium.

1.4. Empirical Performance of the CAPM and FF Models

We now check whether a single factor model like the CAPM can rationalize the returns on the size- and value-based strategies represented by the 16 sorted portfolios in our sample and compare it to the FF model. We estimate the regression

$$(R^p - R_f)_t = \alpha^p + \beta^p_{MK} (R_m - R_f)_t + \beta^p_{HML} HML_t + \beta^p_{SMB} SMB_t + \varepsilon^p_t \qquad (1)$$

where the term on the left is the excess portfolio return, the term $(R_m - R_f)$ is the market excess return and β_{MK} is the market beta, SMB and HML are the FF additional risk factors, and β_{HML} and β_{SMB} are the corresponding regression coefficients. Omitting the additional HML and SMB factors results in the CAPM, other ways we have the FF model.

In the regression (1), p = 1, 2, …, 16 indicates portfolios, t = 1, 2, …, 216 indicates monthly observations.

Since the time series regressions are in excess return form, if the model holds the intercept α^p should be statistically indistinguishable from zero. So, we test the hypothesis H_0: $\alpha^p = 0$. In Table 8 we see the results for the one-factor model (CAPM) applied to equally weighted returns. In the different panels, estimated coefficients correspond to portfolios according to the structure described in Table 3. The market index excess return is always highly significant in explaining the size and value strategy returns, but much less so for small size portfolios P1-P4, represented in the first row of each panel of the Table 8. The R^2 of the regressions clearly increase with size, with the first portfolio (P1, small/growth) showing the lowest value, 0.17. The hypothesis H_0 is seldom rejected. However, when we look at the point values of the β_{MK} coefficients and compare them with the average returns of the portfolios from Table 4, we do not see the positive linear association that the CAPM predicts, that is the CAPM is unable to characterize the expected return of size and value-based strategies in our sample. The left scatter of Figure 1 shows a lack of any positive linear association between the average return on the equally weighted strategies and their market beta for this sample, hence the CAPM produces inconsistent results.

Table 8: *CAPM regression results - equally weighted*

α	Growth	→		Value
Small	0.00694	0.00328	0.00784	0.01153
	(0.86)	(0.99)	(**2.25**)	(**2.99**)
↓	0.00120	0.00168	0.00230	0.00664
	(0.39)	(0.69)	(0.88)	(**2.17**)
	0.00392	0.00693	0.00646	0.00647
	(1.54)	(**2.83**)	(**2.70**)	(**2.32**)
Big	0.00319	0.00406	0.00452	0.00441
	(1.43)	(**2.48**)	(**2.75**)	(**2.05**)
β_{MK}	**Growth**	**→**		**Value**
Small	0.89626	0.75885	0.75571	0.76246
	(**7.71**)	(**14.24**)	(**11.62**)	(**12.35**)
↓	0.89830	0.73593	0.74674	0.78654
	(**17.40**)	(**17.71**)	(**14.79**)	(**13.46**)
	0.77439	0.77945	0.76073	0.90947
	(**16.75**)	(**16.51**)	(**17.71**)	(**18.53**)
Big	0.92307	0.79239	0.86343	1.13058
	(**18.61**)	(**22.62**)	(**26.78**)	(**25.74**)
R^2	**Growth**	**→**		**Value**
Small	0.17	0.47	0.44	0.40
	0.59	0.60	0.57	0.53
↓	0.61	0.63	0.63	0.64
Big	0.74	0.79	0.82	0.82

Note: The result of the OLS regression of the CAPM $(R^p - R_f)_t = \alpha^p + \beta^p_{MK} (R_m - R_f)_t + \varepsilon^p_t$ for the value- and size-sorted portfolios p = 1,2,…,16 over the sample period June 2000 to June 2018, using monthly equally weighted returns. In the model $(R^p - R_f)_t$ is the excess return of the sorted portfolio in month *t*, and $(R_m - R_f)_t$ is the excess return on the market. In parenthesis are reported the t-statistics of the coefficients computed using robust standard errors.
Abbreviation: CAPM, capital asset pricing model.

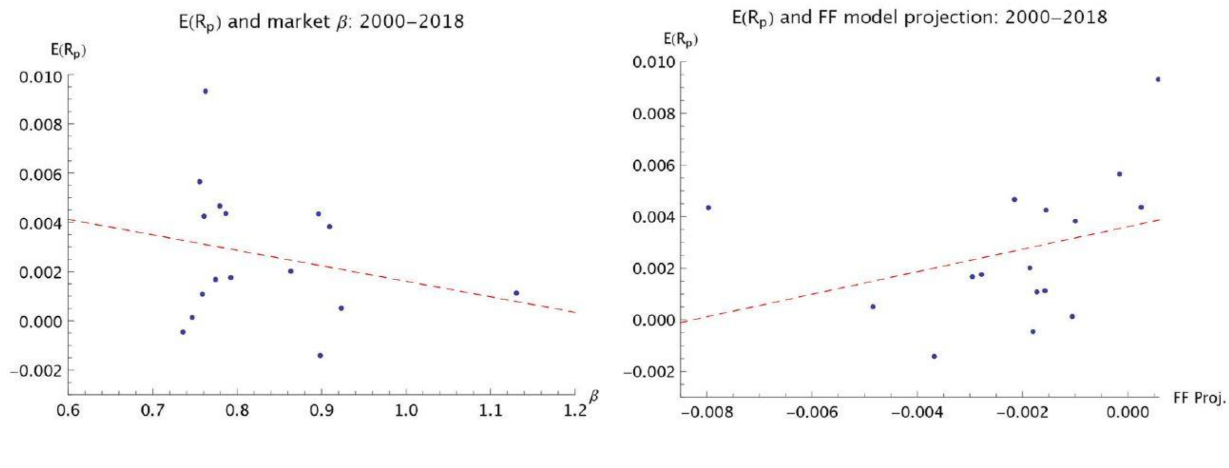


Figure 1 *CAPM and FF Model 2000-2018 - Equally Weighted. The scatter on the left depicts, on the y axis, the average return on the 16 portfolios as in Table 4 against, on the x axis, the betas from the CAPM. In the scatter on the right the same average returns are plotted against the projection* $\beta_{MK}\ \lambda_{MK} + \beta_{HML}\ \lambda_{HML} + \beta_{SMB}\ \lambda_{SMB}$ *from the FF model*

(1) on the x axis. The dashed line is the OLS fit. CAPM, capital asset pricing model. HML, high book-to-market stocks and low book-to-market stocks; SMB, small and big stocks.

In Table 9 we show the results of the FF model applied to the same equally weighted portfolio returns. The fit of the regression is materially improved. The coefficient on the size factor SMB is significant in all cases except for two big stock portfolios (P14 and P16) in the last row of the panel, and its values tend to decrease as size increases, as expected. Coefficients on HML are more variable in significance, although they are clearly positive and significant for value portfolios (P4, P8, P12, P16) and negative for growth portfolios (P1, P5, P9, P13).

Table 9: *FF Model regression results - equally weighted*

α	Growth	$\longrightarrow$	Value	
Small	0.01129	0.00172	0.00472	0.00769
	(**1.96**)	(0.69)	(1.72)	(**2.87**)
	0.00118	0.00021	0.00007	0.00306
	(0.39)	(0.09)	(0.03)	(1.46)
$\downarrow$	0.00349	0.00569	0.00468	0.00380
	(1.34)	(**2.41**)	(**2.04**)	(1.44)
Big	0.00423	0.00339	0.00278	0.00175
	(**2.13**)	(**2.09**)	(1.75)	(0.84)
β_{MK}	**Growth**	$\longrightarrow$	**Value**	
Small	1.14792	0.85278	0.83510	0.86002
	(**13.12**)	(**19.98**)	(**16.87**)	(**17.94**)
	0.95944	0.78243	0.80997	0.86167
	(**20.04**)	(**19.60**)	(**20.35**)	(**20.03**)
$\downarrow$	0.81419	0.81061	0.79174	0.94889
	(**18.12**)	(**17.18**)	(**19.39**)	(**21.89**)
Big	0.92892	0.80352	0.87988	1.14683
	(**22.53**)	(**23.56**)	(**27.57**)	(**30.79**)
β_{HML}	**Growth**	$\longrightarrow$	**Value**	
Small	-1.42737	0.06261	0.44424	0.62214
	(**-2.90**)	(0.76)	(**4.69**)	(**6.03**)
	-0.29892	0.04773	0.23045	0.56714
	(-1.58)	(0.46)	(**3.56**)	(**7.79**)
$\downarrow$	-0.20001	0.00355	0.13247	0.36674
	(-1.58)	(0.04)	(1.73)	(**2.85**)
Big	-0.53586	-0.13178	0.13838	0.39392
	(**-7.55**)	(**-2.71**)	(**3.22**)	(**3.54**)
β_{SMB}	**Growth**	$\longrightarrow$	**Value**	
Small	2.70003	1.13188	1.12669	1.37790
	(**5.60**)	(**9.85**)	(**9.92**)	(**12.33**)
	0.60160	0.54686	0.82516	1.05831
	(**3.55**)	(**5.01**)	(**9.96**)	(**13.30**)
$\downarrow$	0.33053	0.27365	0.32645	0.48962
	(**2.62**)	(**3.01**)	(**3.72**)	(**3.60**)
Big	-0.26489	-0.03556	0.12665	0.16112
	(**-3.47**)	(-0.58)	(**2.23**)	(1.47)
R^2	**Growth**	$\longrightarrow$	**Value**	
Small	0.74	0.71	0.67	0.71
	0.69	0.68	0.73	0.77
$\downarrow$	0.66	0.65	0.66	0.70
Big	0.81	0.81	0.83	0.86

Note: The result of the FF model $(R^p - R_f)_t = \alpha^p + \beta^p_{MK} (R_m - R_f)_t + \beta^p_{HML} HML_t + \beta^p_{SMB} SMB_t + \varepsilon^p_t$ for the value- and size-sorted portfolios p = 1,2,…,16 over the sample period June 2000 to June 2018, using monthly equally weighted returns. In the model $(R^p - R_f)_t$ is the excess return of the sorted portfolio in month *t*, and $(R_m - R_f)_t$ is the excess return on the market, HML_t and SMB_t are the additional FF factors. In parenthesis are reported the t-statistics of the coefficients computed using robust standard errors. Significant values at 5% or less are in bold.

When we look at the ability of the FF model to account for average return in the cross section of equally weighted portfolios, the scatter on the right of Figure 1 shows some positive linear association between average returns and the projection of the three risk factors of the FF model. The fit is however visibly altered by the leftmost point, which represents portfolio P1, small/growth. We note in the comment to the descriptive statistics in Section 3 that the return of this portfolio containing the smallest stocks has somewhat erratic behavior.

When we consider value weighted strategies, the results of the regressions reported in Tables 10 and 11 show the different performance of the two models. The single factor model (CAPM) produces better results for small size value weighted portfolios compared to the equally weighted case, once the smallest stocks are given less weight (the R^2 on the first small/growth portfolio increases from 0.17 to 0.48), but the additional HML and SMB factors of the FF model add explanatory power for the strategies, producing a marked increase in R^2 throughout the 16 portfolios. The SMB factor is significant for all but two of the largest size portfolios, while the HML factor coefficient is positive and significant for value strategies and negative for growth strategies. Again, the single beta model does not explain the cross section of average returns on the strategies. The left scatter of Figure 2 shows a negative linear relationship between average value weighted returns on the 16 strategies and their beta on the market, which is not compatible with the CAPM, while, in the right scatter, the prediction from the FF model provides a linear cross-sectional fit with positive slope.

Table 10: *CAPM regression results - value weighted*

α	Growth $\longrightarrow$ Value			
Small	-0.00225	0.00252	0.00863	0.01122
	(-0.54)	(0.71)	(**2.14**)	(**2.44**)
	0.00029	0.00239	0.00015	0.00515
	(0.09)	(0.93)	(0.05)	(1.58)
	0.00154	0.00511	0.00582	0.00344
↓	(0.58)	(1.89)	(**2.34**)	(1.19)
Big	0.00288	0.00235	0.00437	0.00334
	(1.24)	(1.23)	(**2.51**)	(1.41)
β_{MK}	**Growth $\longrightarrow$ Value**			
Small	0.97063	0.74343	0.79570	0.77821
	(**10.22**)	(**12.96**)	(**10.42**)	(**10.28**)
	0.90460	0.73522	0.77441	0.78697
	(**16.55**)	(**16.15**)	(**13.67**)	(**12.65**)
	0.76409	0.80991	0.76320	0.95736
↓	(**16.93**)	(**15.81**)	(**17.45**)	(**18.44**)
Big	0.92325	0.84948	0.83069	1.14313
	(**17.60**)	(**15.75**)	(**23.97**)	(**22.98**)
R^2	**Growth $\longrightarrow$ Value**			
Small	0.48	0.42	0.39	0.33
	0.58	0.57	0.53	0.49
↓	0.58	0.60	0.61	0.64
Big	0.72	0.77	0.79	0.79

Note: The result of the OLS regression of the CAPM $(R^p - R_f)_t = \alpha^p + \beta^p_{MK}\ (R_m - R_f)_t + \varepsilon^p_t$ for the value- and size-sorted portfolios p = 1,2,…,16 over the sample period June 2000 to June 2018, using monthly equally weighted returns. In the model $(R^p - R_f)_t$ is the excess return of the sorted portfolio in month *t*, and $(R_m - R_f)_t$ is the excess return on the market. In parenthesis are reported the t-statistics of the coefficients computed using robust standard errors. Significant values at 5% or less are in bold.
Abbreviation: CAPM, capital asset pricing model.

Table 11: *FF Model regression results - value weighted*

α	Growth → Value			
Small	-0.00090	0.00280	0.00825	0.01041
	(-0.24)	(0.94)	(**2.48**)	(**2.76**)
↓	0.00367	0.00340	-0.00005	0.00393
	(1.39)	(1.47)	(-0.02)	(1.56)
	0.00350	0.00537	0.00519	0.00114
	(1.44)	(**1.98**)	(**2.12**)	(0.43)
Big	0.00495	0.00343	0.00365	0.00075
	(**2.32**)	(1.79)	(**2.17**)	(0.34)
β_{MK}	**Growth → Value**			
Small	1.05144	0.81070	0.87000	0.86313
	(**11.75**)	(**14.77**)	(**14.37**)	(**13.60**)
↓	0.98193	0.78443	0.82230	0.83867
	(**21.38**)	(**19.27**)	(**17.92**)	(**17.46**)
	0.81490	0.82791	0.77141	0.95456
	(**20.11**)	(**15.91**)	(**18.59**)	(**19.98**)
Big	0.92924	0.86435	0.83135	1.12139
	(**20.03**)	(**16.67**)	(**25.11**)	(**26.15**)
β_{HML}	**Growth → Value**			
Small	-0.08522	0.12767	0.30161	0.43357
	(-0.69)	(1.30)	(**2.77**)	(**3.25**)
↓	-0.56801	-0.09507	0.18506	0.43312
	(**-4.96**)	(-1.35)	(**2.33**)	(**5.30**)
	-0.31111	-0.01046	0.17098	0.52791
	(**-4.08**)	(-0.10)	(1.84)	(**5.81**)
Big	-0.46415	-0.20901	0.17038	0.54214
	(**-6.81**)	(**-3.35**)	(**3.23**)	(**7.02**)
β_{SMB}	**Growth → Value**			
Small	1.27663	1.15219	1.34469	1.57692
	(**9.78**)	(**5.36**)	(**8.37**)	(**8.57**)
↓	1.00248	0.75791	0.86255	1.03630
	(**9.38**)	(**6.79**)	(**7.97**)	(**9.24**)
	0.68677	0.28809	0.21058	0.19218
	(**6.23**)	(**2.10**)	(1.88)	(1.89)
Big	-0.11163	0.14772	0.08759	-0.10944
	(-1.32)	(1.72)	(1.16)	(-1.41)
R^2	**Growth → Value**			
Small	0.62	0.60	0.61	0.60
↓	0.74	0.67	0.66	0.69
	0.67	0.61	0.63	0.70
Big	0.77	0.79	0.80	0.84

Note: The result of the FF model $(R^p - R_f)_t = \alpha^p + \beta^p_{MK} (R_m - R_f)_t + \beta^p_{HML} HML_t + \beta^p_{SMB} SMB_t + \varepsilon^p_t$ for the value- and size-sorted portfolios p = 1,2,…,16 over the sample period June 2000 to June 2018, using monthly equally weighted returns. In the model $(R^p - R_f)_t$ is the excess return of the sorted portfolio in month *t*, and $(R_m - R_f)_t$ is the excess return on the market, HML_t and SMB_t are the additional FF factors. In parenthesis are reported the t-statistics of the coefficients computed using robust standard errors. Significant values at 5% or less are in bold.

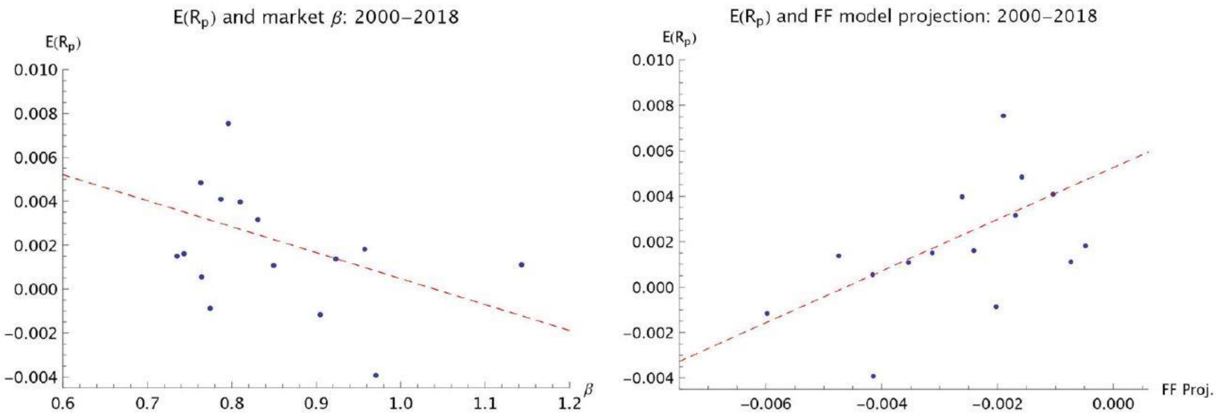


Figure 2 *CAPM and FF Model 2000-2018 - Value Weighted. The scatter on the left depicts, on the y axis, the average return on the 16 portfolios as in Table 5 against, on the x axis, the betas from the CAPM. In the scatter on the right the same average returns are plotted against the projection* $\beta_{MK}\ \lambda_{MK} + \beta_{HML}\ \lambda_{HML} + \beta_{SMB}\ \lambda_{SMB}$ *from the FF model (1) on the x axis. The dashed line is the OLS fit. CAPM, capital asset pricing model; HML, high book-to-market stocks and low book-to-market stocks; SMB, small and big stocks.*

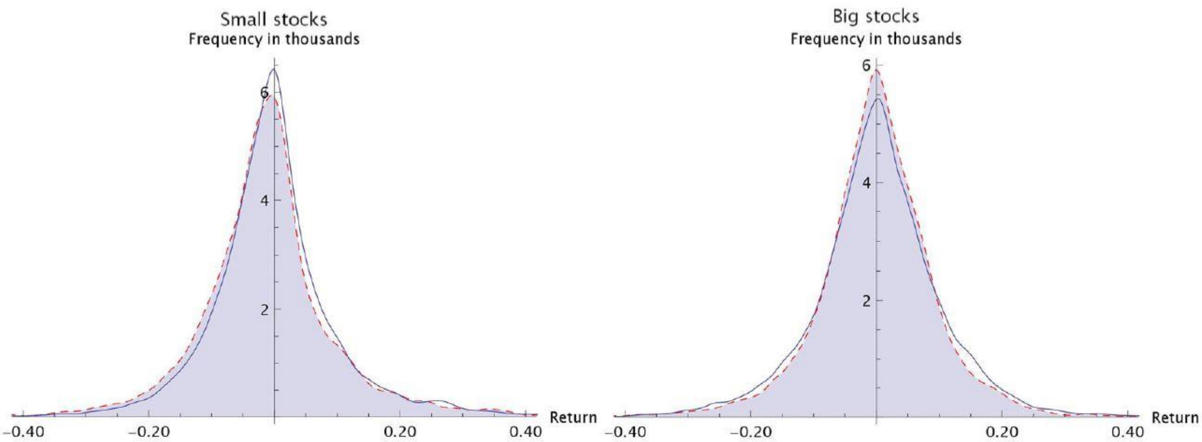


Figure 3 *Frequency distribution of returns for Growth and Value stocks. The dashed line, along the shaded area, represents the frequency distribution of returns on Growth stocks, the solid line the frequency distribution of returns on Value stocks. Sample period 2000-2018.*

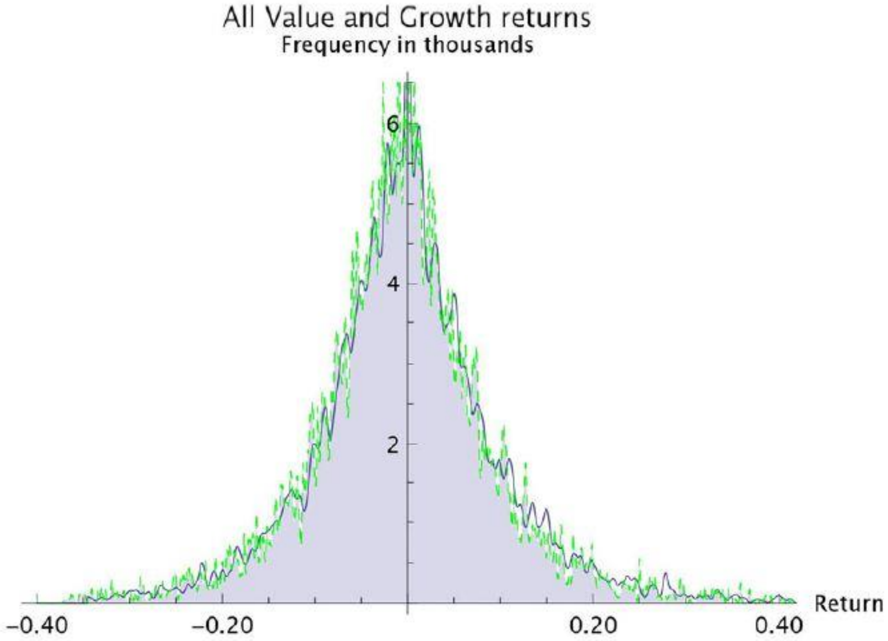


Figure 4 *Frequency distribution of returns for Growth and Value stocks. The dashed line, along the shaded area, represents the frequency distribution of returns on Growth stocks, the solid line the frequency distribution of returns on Value stocks. Sample period 2000-2018.*

1.4.1. Analysis of the HML factor

The pricing impact of the SMB factor, which characterizes a strategy of going long on small stocks and short on large stocks, is usually linked to the specific risks of small stocks, mostly their lack of liquidity and their lower resilience to downturns in the business cycle. Given the importance of small stocks in the Italian Stock Market, it is not surprising that the SMB factor plays an important role in explaining stock returns, as already established in the literature discussed in the Introduction. In the down market we analyzed, the risk premium for the size strategy is not unequivocally positive.

On the other hand, in the 2000-2018 sample the value-based strategy produces high positive returns. The HML factor, which characterizes the strategy of going long on high B/M stocks and short on low B/M stocks, has an associated risk premium of 4.8% on a yearly basis in the 2000-2018 equally weighted sample, and a risk premium of 5.4% on a yearly basis in the value weighted sample, more than twice its standard deviation. In what follows we try to look at the determinants of its returns by examining in more detail the statistical properties of the returns of value and growth stocks in the sample.

We took the returns of all stocks in the 30% top and bottom percentiles of the HML factor sorting and looked at their frequency distribution.

The large mean return of the equally weighted HML factor in Table 6 comes from the difference between the mean return of all value stocks and all growth stocks included in the HML factor. In turn, the mean return of value and growth stocks is the sum of returns on small and big value and growth stocks. The frequency distribution of these returns helps to understand the differences in average returns of value and growth strategies.

Table 12: *Frequency distribution of value and growth stock returns*

	$x < -0.2$	$-0.2 < x \leq -0.1$	$-0.1 < x \leq -0.05$	$-0.05 < x \leq 0$	$0 < x \leq 0.05$	$0.05 < x \leq 0.1$	$0.1 < x \leq 0.2$	$0.2 < x$	Average x	Count
Small Growth	.039	.115	.151	.252	.203	.092	.075	.048	-.001	7629
Small Value	.026	.088	.136	.242	.207	.111	.074	.050	.006	7750
Big Growth	.027	.083	.130	.246	.246	.145	.088	.023	.001	8513
Big Value	.032	.096	.129	.220	.227	.136	.107	.031	.003	8489
All Growth	.033	.098	.140	.249	.226	.120	.082	.035	.000	16142
All Value	.029	.093	.134	.233	.219	.125	.092	.040	.004	16239

In particular, from Figures 3 and 4 and from Table 12 we see that value stocks have a somewhat higher frequency of large returns between 10 and 20 percent and growth stocks have a higher frequency of both small (0 to minus 5 percent) and large negative returns. When we consider small and big stocks separately (Figure 3), small growth stocks have a higher frequency of negative returns throughout the support, and small value stocks have more positive returns in the range 5 to 10 percent, while big value stocks have more positive returns between 10 and 20 percent. Table 13 reports average returns by year, which are generally of the same sign as the stock index return with a tendency for value stocks to do better than the market.

Table 13: *Mean return of value and growth components of HML by year*

Year	SG	SV	BG	BV	Rm
2000-2001	- .009	.009	- .020	.005	- .017
2001-2002	- .025	- .009	- .023	- .011	- .021
2002-2003	- .014	.000	- .009	- .008	- .007
2003-2004	.000	.011	.013	.024	.011
2004-2005	.015	.030	.013	.027	.012
2005-2006	.018	.017	.007	.016	.010
2006-2007	.018	.039	.011	.027	.012
2007-2008	- .049	- .027	- .048	- .040	- .028
2007-2008	- .013	- .019	- .011	- .026	- .031
2009-2010	- .002	- .007	.003	.004	.003
2010-2011	.006	.007	.011	- .001	.006
2011-2012	- .029	- .034	- .014	- .034	- .025
2012-2013	.016	.013	.017	.025	.007
2013-2014	.032	.059	.024	.043	.029
2014-2015	- .004	.000	.018	.008	.005
2015-2016	- .036	- .020	.000	- .021	- .025
2016-2017	.070	.028	.029	.023	.021
2017-2018	.005	.015	.009	- .005	.005

Note: SG denotes the return on the small/growth component of HML, SV the return on the small/value component, BG the return on the big/growth component, BV the return on the big/value component, Rm is the return of the stock index. Abbreviation: HML, high book-to-market stocks and low book-to-market stocks.

When we looked at the high returns of value stocks from a qualitative point of view, we found many cases in which the high positive return was associated with a merger-arbitrage event (mergers, acquisitions), unexpected positive reporting by the company or company turnaround plans that occasionally produced large changes in price. Such returns involve risks which are not fully described by general market risk but are not idiosyncratic either. Our conjecture is that a very high risk premium recorded for value stocks during the sample period is partly due to these events.

1.5. Conclusion

We investigated the risk return characteristics of size- and value-based trading strategies in the Italian stock market in the 2000-2018 sample period.

We used data from Borsa Italiana and Mediobanca in order to correctly define value- and size-based strategies and the HML factor. Unlike previous studies, our analysis is based on all available stocks, rather than partial samples.

In the sample period, the time series of the return on these strategies are poorly explained by a single factor model, and in the cross section, average returns are not positively related to market beta, contradicting the CAPM. This result is in line with previous evidence and requires the definition of additional risk factors to rationalize the observed returns on these strategies. The HML and SMB factors proposed by Fama and French (1993) help explain the returns on value- and size-based strategies in a consistent way. The R^2 of the FF model is consistently higher than that of the CAPM for every strategy. In the FF model, the return on small stock portfolios is significantly and positively associated with SMB, and the return on value portfolios is significantly and positively associated with HML.

While previous research did not confirm the pricing relevance of the HML factor, we show its significance in pricing aggregate stock returns in our sample.

In the 2000-2018 period, in which the stock market showed a negative return, the risk premium of the value-based strategy represented by HML is considerable, and about 5% annualized. By analyzing the distribution of the individual components of this return in detail, we find that it can be attributed to a large extent to a higher frequency of large returns on value stocks. This pattern is compatible with the idea that value stocks are subject to turnaround, acquisitions, and merger-arbitrage activities, which occasionally produce large changes in price.

CHAPTER 2. Asset Pricing and Industrial Electricity Usage

Pursuing the aim of finding new business cycle predictors of future stock returns, the study in this chapter uses the industrial electricity usage variable to predict the fluctuations in Italian stock market inspired initially by the work of Zhi Da et al. (2017). The reason for using industrial electricity usage for this matter lies in the difficulty in storing energy. Therefore, the logic suggests that the changes in energy consumption can be used to track industrial production in real time. Real business cycle variables, like production, comove with stock market returns. Zhi Da et al. (2017) show that industrial energy usage performs optimally in the prediction of US stock returns. However, despite the previous encouraging results, a deeper understanding of the industrial technologies used in the production process suggests that the matter is not so simple. The reason for this can be found in the concept of energy efficiency of the equipment that plants use. A comparable measure of energy efficiency is the intensity of energy consumption which is the ratio of the total final energy consumption (in GJ) and the value added at constant price. Another possible efficiency measure is the specific energy consumption per unit of the product. Moreover, the energy efficiency is closely linked to the analysis of the carbon footprint (emissions of greenhouse gases (GHG)) that each firm leaves during its production process, with special attention paid to the emissions of CO2. So, the task of this work is to check whether the industrial electricity usage variable can predict future Italian stock returns, either alone or after the correction using one or more energy efficiency measures.

2.1. Literature Review

2.1.1. Production-based Asset Pricing and Industrial Electricity Usage

Prediction of stock market returns is a central issue in asset allocation, risk, and portfolio management. However, the use of business cycle variables for this matter is usually less preferred compared to the financial variables due to the former's weak performance. This study attempts to identify a real variable capable of competing with financial variables in the explanation of stock returns, based on the connection between key inputs of the production function of each firm and the sector stock market returns.

Generally speaking, the matter of the linkage between the production function and stock returns is not new and was largely investigated by many economists, starting with Cochrane (1991,1993, 1996, 2005 and other papers) who elaborated on asset pricing with production data.

The underlying setting is characterised by perfect competition, compete markets and neoclassical environment (Y=*f* (L, K, productivity shocks) as in RBC models).

The consumption-based asset pricing was taken as the point of departure for this theory mostly because in it the discount factor (*m*) could be inferred without solving any type of equilibrium problems, neither partial, nor general. The approach used here, following the production-based asset pricing theory by Cochrane (1991 and the subsequent works), links the discount factor to the marginal rates of transformation (instead of the marginal rates of substitution as for the consumption-based version) of output across states and is valid for any type of preferences. The production set is smooth, and the technology of the production process is without kinks. The asset pricing equation under consideration is of the following form:

$$E_{t-1}\,[m_t\,R_t^e] = 0 \qquad (2)$$

Where *m* is the discount factor (or the pricing kernel), R^e is the asset return net of the risk-free rate. The equation literally reads that the excess stock returns have a zero mean.

As Balvers and Huang (2006) point out, the pricing kernel *m* is in real terms, hence, the return should be either corrected for inflation or taken as the excess return. As most authors, Balvers and Huang (2006) choose to use excess returns. By decomposing the equation (2), one may write:

$$E_{t-1}\,[R_t^e] = -\frac{Cov_{t-1}\,(m_t,\ R_t^e\,)}{E_{t-1}[m_t]} \qquad (3)$$

And, therefore, the mean excess return depends on the covariance of excess returns with the discount factor *m*.

According to the production-based asset pricing, the discount factor *m* is a function of production factors (output, investment, capital stock, inventories etc.), or firm's productivity. In Balvers and Huang (2006) it is modelled as follows:

$$m = \lambda\,\frac{\varepsilon^{\alpha}}{\theta^{1+\alpha}} \qquad (4)$$

where λ is the constant Lagrange multiplier, ε is the state-contingent level of productivity, θ is the level of natural productivity, α > 1 plays the role similar to the risk aversion coefficient in the utility theory - it ensures the strict concavity (and smoothness) of the production possibilities frontier.

The dynamic version of the last equation which links the discount factor to productivity growth is:

$$m_{t+1} = \lambda_t \left(\frac{\varepsilon_{t+1}}{\varepsilon_t}\right)^{\alpha} \left(\frac{\theta_{t+1}}{\theta_t}\right)^{-(1+\alpha)} \quad (5)$$

By following Belo (2010), Cochrane (2020) generalises the investment-return models considering the possibility of endogenous decision on the productivity level and the level of natural productivity for each producer. In this setting ε and θ are chosen by the producer for each state.

Essentially, these authors state that stock returns are linked to the discount factor through the productivity growth which is a complex result of the output, investment growth, working hours and some other production inputs.

Hence, the search for a variable capable of predicting asset prices most precisely brings many scholars of asset pricing to directly consider the industrial production index, strictly correlated to the real economy, as the leading predictor.

Still, there is another aspect to be considered when making decisions in financial markets, which is timing. Prediction of future stock market returns by using the industrial production, a lagged variable not available at high frequency, may expose the market participants to the risk of information asymmetries, which give rise to timing issues, and, thus, may make the forecasting objective unreachable.

Some economists such as Bodo and Signorini (1987, 1991) pointed out the timing problem on the basis of Italian data. In their articles it is the starting point of analysis that tries to estimate the industrial production index in Italy, or better, to forecast it in the short-term. The main concern is which variable must be employed to predict the industrial production, that would remove or effectively mitigate the timing problem which arises when a “lagged variable” is used. Bodo and Signorini chose the electric energy consumption. At that time this variable was published by Enel s.p.a. more promptly than the industrial production index. So, the authors tried to forecast Italian industrial production index based on the energy data provided by Enel s.p.a., which they adjusted for seasonality applying the concept of energy degree-days (EDD)[4]. The corrected series were then tested with the ARIMA (the autoregressive integrated moving average) model which is known to provide forecasts on a non-stationary data series. In this model the predictor variables are lagged, and the error term is a random variable. Speaking in economic terms, such error term can be

[4] Energy Degree Days are the days when the outside temperature is either very high or very low with respect to the standard (20°C for Italy before 2022). This fact leads to higher consumption of energy either to heat or to cool the indoor environment. The relationship between energy consumption and temperature has a U-shape form, having peaks of consumption at the ends of the temperature range and the minimum in the point of conventional “comfortable” temperature (20°C in Italy).

considered as a shock in the market. After the ARIMA analysis the authors used a business survey on the expectation of future industrial production to countercheck the results. This choice was forced by the availability of the data. At the time of Bodo & Signorini's study, the institution which provided this type of information, ISCO (Istituto Nazionale per lo Studio della Congiuntura), published survey results twenty days before the issue of the production index thereby mitigating the timing problem. The conclusion which Bodo *et al.* draw in their work is that the forecast of industrial production using electric energy consumption combined with a business survey can lead to satisfactory results.

At that point, having the industrial production as the main predictor of asset returns, it may be reasonable to expect that the electricity consumption explains stock returns too.

In this respect, it is useful to refer to the article by Zhi Da *et al.* (2017), where the authors explained how electric energy consumption data could be used to achieve this goal. In fact, that work presented an analysis which aimed at estimating the explanatory power of electric energy consumption over the U.S. stock market, comparing the results with other models that use such variables as Output growth, Capacity utilisation, Dividend-Price ratio, Book-to-Market ratio, Inflation, and long-term Interest rates. Summing up, the study produced quite satisfactory results as referred to the U.S. market, even outperforming some financial models. Whether the results will be the same for the Italian market is the question that this research is trying to answer.

Neither Zhi Da *et al.* (2017), nor Bodo and Signorini (1987, 1991) used aggregate national raw data on electric energy consumption in their studies. Their interest was only in the industrial energy consumption, and the inclusion of the share of domestic energy consumption, strongly affected by seasonality among other issues, would most probably make the statistical results unreliable. Eventual increases in energy consumption of the domestic sector, either due to seasonality or not, do not depend on a greater production at industrial level. Besides, seasonal increases in energy consumption of the industrial sector do not reflect changes in sector productivity. Therefore, seasonality and domestic energy consumption were removed from the data series subject to analysis.

The difference between the works of the authors lies in the final output: Zhi Da *et al.* (2017) estimated the excess stock return using electricity consumption and industrial production as predictors; while Bodo *et al.* (1987, 1991) tried to explain the Italian industrial production index, considered as the dependent variable. Therefore, the aim of Bodo *et al.* (1987, 1991) was limited to understanding how the energy consumption fluctuations affected the industrial production, while Zhi Da *et al.* (2017) wanted to understand how these shifts affected the stock market. The actual difference is that Bodo *et al.* made their work considering just the real economy variables. Conversely, Zhi Da *et al.* (2017)

wanted to understand the effect, which a real variable could produce on financial markets, more precisely on the stock market, filling up the gap between "the asset pricing literature and the business cycle one". The results presented in Zhi Da *et al.* (2017) for the U.S. market are in line with the idea of a countercyclical market risk premium. The electricity growth has a negative coefficient, which is consistent with the above-mentioned theory. The reason for that is the fact that in a market recession the expected returns for an investor will be higher to compensate them for the risk of investment in an underperforming stock; on the contrary, when a stock is performing well, following for instance an expansion of the market, the premium requested by a risk-averse investor is lower than in the first case. This idea is explained well by Fama and French (1989).

The results obtained by Zhi Da *et al.* (2017) for the US stock market seem to confirm the predictive power on stock returns of such real variable as industrial electricity usage. In the present work these models are tested on the Italian data.

The timing is an issue also for the Italian data: the industrial production index is issued by Istat (*Istituto Nazionale di Statistica*, the Italian National Statistical Institute) with a delay of one – one and a half months which means that it is impossible to track production data in real time. Therefore, monthly stock returns cannot be associated with the contemporaneous industrial production data point. However, Terna spa[5], the grid operator for electricity transmission in Italy, provides detailed hourly information on the withdrawals in different Italian operational areas from the national electricity grid. It publishes their own index IMCEI (Monthly Industrial Electrical Consumption Index), a proxy of the Industrial Production Index, both in month-over-month and year-over-year versions. It is issued at the end of each month based on the data of that month. Industrial electricity consumption data at annual level are freely available on Terna's website, monthly industrial data are available upon special request. The electricity consumption data have a better timing and, hence, can be associated with contemporaneous stock returns.

2.1.2. Variable Capital Utilisation Model (BER 95)

One of the main reference articles for the theoretical foundation of the present research is the one by Burnside, Eichenbaum and Rebelo (1995) (BER 95) who presented the theory of direct correlation between procyclical capital utilisation rates and cyclical changes in labour productivity for different degrees of returns to scale. In their study the growth in capital utilisation was approximated by industrial electricity usage and capital workweek. The authors made a direct

[5] www.terna.it

comparison with the empirical finding of the real business cycle model (the Solow residual as the measure of capital services).

The paper addressed the puzzle of a seeming statistical insignificance of capital in explaining changes in output. To this regard BER 95 proposed a better measure for capital services, the industrial electricity usage, which produced better inference results.

The authors emphasized the importance of their measure in affecting cyclical labour productivity and the latter being the main cause of economic fluctuations. This thought was borrowed from the RBC models.

BER 95 put emphasis on cyclical movements of capital utilisation and labour hoarding by following the trend of such authors as Greenwood, Hercowitz and Huffman (1988), Kydland and Prescott (1988), Burnside, Eichenbaum and Rebelo (1993), Finn (1991), Basu and Kimball (1994), Bils and Cho (1994), and Burnside and Eichenbaum (1994).

In order to find out if the new measure was a good candidate to be the source of procyclical productivity, the authors analysed the properties of the Solow residual and estimated the degree of returns to scale. Usually, variants of Hall's (1988) invariance test[6] applied to annual data are used for this purpose. The authors chose to use annual data in conjunction with different specifications of production technology. In this way the estimated residuals differed from the traditional Solow residual and produced a different conclusion of Hall's test: the residuals in BER 95 passed this test while the common Solow residual did not pass it. Besides, the obtained residuals were much less volatile and less correlated with the aggregate output than those used in RBC literature. Therefore, RBC measure of technology shocks turned out to be implausible as a driver of the aggregate output.

The measure of aggregate electricity consumption in BER 95 is a quarterly average of a monthly index of industrial energy usage, which includes manufacturing, mining, and utility industries. This index is provided in the Federal Reserve Statistical Release and is measured in kilowatts of electricity. Three sources of data are used to construct this index: measures of physical product, kilowatt-hours of electricity and production worker hours.

The specifications of technology that authors used in their study are the following:

$$Y_t = min\ (M_t, V_t) \tag{6}$$

[6] The invariance of the Solow residual refers to the proposition that under certain conditions, such as competition and constant returns to scale, this residual is uncorrelated with the variables that are uncorrelated with the productivity shifts.

Where Y_t is gross output at time t, M_t are materials at time t, V_t (value added) is a function of worked hours (L_t), capital stock (K_t) and electricity usage (E_t) ($V_t = V(L_t, K_t, E_t)$). The relation between capital services and electricity usage is by way of Leontief technology (<u>weak or no substitutability between factors</u>). The same fixed-coefficients relationship is also imposed between M_t and V_t.

The data frequency is quarterly and annual. No assumptions are made about goods and factor markets.

In this setting the value added produced in one hour by each worker is equal to: $A_t F(1, K_t/N_t)$
F (·) is a concave twice differentiable homogeneous function of degree one. N_t is the number of workers at time t, A_t is the state of technology (and other exogenous factors that affect productivity) at time t.

If $N_t H_t$ denotes the total hours which all N_t workers worked in period t, then the total value added produced by a certain firm in a given period t will be:

$V_t = N_t H_t A_t F(1, K_t/N_t) = A_t F(N_t H_t, K_t H_t)$ where H_t is the workweek of a capital good *(7)*

In order to have a measure of capital services $K_t H_t$ at quarterly frequency BER 95 followed the idea of Griliches and Jorgenson (1967) and Costello (1993) who used electricity usage as an indirect measure of capital services in their studies.

If industrial electricity usage per machine is proportional to H_t, then $E_t = \varphi H_t K_t$ where E_t is total electricity consumption. This representation of E_t works around the main criticism of using electricity as a measure of capital services: the possible non-stationarity of the electricity-capital ratio. If φ is a deterministic function of time, the problem does not arise.

Denoting $L_t = N_t H_t$ will lead to: $Y_t = A_t F(L_t, E_t / \varphi)$ *(8)*

Here all the data are available quarterly.

This setting has just one drawback: it assumes that the elasticity of E_t with respect to K_t is equal to unity, which in reality may not be so due to different reasons, one of which is the overhead capital. This assumption is relaxed in the generalised version of technology presented further.

The authors also adjusted their representation of industrial electricity consumption to the changes in the intensity of capital usage ("line speed", λ_t), which is by all means a measure of the energy efficiency of the machinery, by making E_t proportional to them:

$$E_t = \varphi \lambda_t H_t K_t \qquad (9)$$

where the product of the first three elements is the effective workweek of the machine.

The value added produced in one hour by each worker is then: $A_t F (1, \lambda_t K_t/N_t)$. (10)

Also considering that electricity consumption per machine is proportional to the effective workweek of the machine, $\varphi \lambda_t H_t$, then E_t is equal to $\varphi \lambda_t H_t K_t$ and the equation $Y_t = A_t F (L_t, E_t/\varphi)$ will remain unchanged. Therefore, the use of the variable electricity consumption to measure capital services allows for the changes in line speed.

The electricity use also depends on labour effort ("labour hoarding" or "labour utilisation"). Therefore, the workweek H_t should be corrected for the effort per hour. Basu & Kimball (1997) studied the concept of labour utilisation closely and deduced that it can partly reflect the variable capital utilisation. The reason for this is shift premia (if there are any) which link worked capital hours and labour compensation. If electricity consumption is used as a proxy for variable capital utilisation, Bils & Cho (1994) found a certain relationship between the former and the worked hours per each worker. Shapiro (1996b) proved that the correlation between capital workweek and labour is generally positive. Nonetheless, it is impossible to deduce in which measure labour effort is a proxy for labour utilisation and in which for capital utilisation. So, for the sake of possibility to compute an econometric analysis, a simplification is due. Therefore, the authors (BER 95) do not include the adjustment for labour effort in their study. In this way they allow for some distortion of their results which favours the rejection of the null hypothesis of constant returns to scale.

1. In order to get to the second specification, the authors first consider a generalised version of technology:

$$Y_t = min\ (M_t, V_t^*) \qquad (11)$$

Where $V_t^* = A_t F(L_t, K_t^*)$ and K_t^* is a constant elasticity of substitution function of capital and electricity use:

$K_t^{*}=[\mu(H_tK_t)^{\rho} + (1-\mu)\, E_t^{\rho}]^{1/\rho} \qquad \rho<1$ (12)

The Leontief relationship between capital services and E_t is relaxed but the no-substitutability is maintained between M_t and V_t. The data frequency is quarterly and annual.

No assumptions are made about goods market. Factor markets (hours worked and electricity) are assumed to be perfectly competitive.

For a price-taking firm in both electric and labour markets, the optimality condition for the firm's demand for electricity requires the equality between the MRS between N_t and E_t and the relative prices, $W_t\, H_t/ P_{Et}$ with W_t being the real wage rate per worked hour at time *t*:

$$\frac{A_t\, F_2(L_t,K_t^{*})(1-\mu)(K_t^{*}E_t)^{1-\rho}}{F_1(L_t,K_t^{*})} = \frac{P_{Et}}{W_t} \qquad (13)$$

where F_i denotes the partial derivative with respect to the *i*th argument of *F*.

The authors assume that the production function is weakly separable between labour and the other factors and that the function F (·) is Cobb-Douglas. Thus:

$$Y_t^{*}= A_t\,(L_t)^{\alpha_1}\,(K_t^{*})^{\alpha_2} \qquad (14)$$

However, at the beginning the production function is not set to be constant returns to scale ($\alpha_1 + \alpha_2 \neq 1$). It is the hypothesis that the authors test.

Given the last two equations, the gross output can be represented by a geometric average of total hours (L_t), energy consumption (E_t), and the price of electricity relative to labour (P_{Et}):

$$Y_t = \left((1-\mu)\, \frac{\alpha_2}{\alpha_1}\right)^{\alpha_2/\rho} A_t\; (L_t)^{\alpha_1+\alpha_2/\rho}\; (E_t)^{\alpha_2-\alpha_2/\rho} P_{Et}{}^{-\alpha_2/\rho} \qquad (15)$$

After taking the first differences and denoting logarithms with lowercase letters they get:

$$\Delta y_t = \gamma_0 + \gamma_1\, \Delta l_t + \gamma_2\, \Delta e_t + \gamma_3\, \Delta p_{Et} + \varepsilon_t \qquad (16)$$

Where $\gamma_0 + \varepsilon_t$ is the growth rate of A_t ; $\gamma_1 = \alpha_1 + \alpha_2/\rho$; $\gamma_2 = \alpha_2 - \alpha_2/\rho$; $\gamma_3 = -\alpha_2/\rho$

This basic production structure coincides with the special case in which the elasticity of substitution between capital and energy is equal to zero ($\rho \to -\infty$) (the first specification).

According to the second specification the equation becomes:

$$\Delta y_t = \gamma_0 + \alpha_1 \, \Delta l_t + \alpha_2 \, \Delta e_t + \varepsilon_t \tag{17}$$

2. The third specification relaxes the Leontief relationship between M_t and V_t. So, Y_t becomes a differentiable function:

$$Y_t = F\,(S_t, L_t, E_t, M_t) \tag{18}$$

The data frequency is annual.

The first-order log-liner approximation of this technology yields:

$$\Delta y_t = \eta \, \Delta x_t + \varepsilon_t \tag{19}$$

Where η denotes overall returns to scale, and Δx_t is a cost-weighted measure of the growth rate of aggregate inputs.

$$\Delta x_t = c_{St} \Delta s_t + c_{Lt} \, \Delta l_t + c_{Mt} \, \Delta m_t + c_{Et} \Delta E_t \tag{20}$$

Here lowercase symbols denote logarithms of upper-case symbols and c_{jt} denotes the share of factor *j* in the total cost, at time *t*.

So, the only technology specification in which the energy input cannot be completely substituted as in Roma and Pirino (2009), is the first one. However, it relies on fixed-coefficients relationship, without considering any possible entropy.

Nevertheless, the inference results about returns to scale on all three specifications are the same: the hypothesis of constant returns to scale is not rejected.

In addition, by following Hall (1988), who did not estimate a production function due to the abovementioned “capital insignificance” puzzle, the authors explore the returns to scale by studying the dependence of changes in output on a cost-weighted sum of growth rates of inputs. By using the new measure of capital services, the result is the same as before, the hypothesis of constant returns to scale is not rejected.

Besides, the authors present evidence that if a measure of capital services refers to capital goods which do not use electricity, overhead labour, overhead capital, and multiple production shifts, the procyclicality of capital services is underestimated. Consequently, the inference regarding the cyclical movements in labour productivity and the degree of returns to scale is inaccurate.

So, the main conclusions that BER 95 make are the following:

1) the empirical results of the tests on manufacturing industry data support the idea of constant (or at least small increasing) returns to scale (the coefficients on labour and capital services that were obtained by the authors are in line with labour and capital shares in the US national income);
2) the RBC idea that changes in output depend only on aggregate technology shocks is not sustained empirically;
3) the cyclicality of electricity-based capital utilisation rates drives the changes in labour and factor productivity.

Therefore, returning to the first part of this section, by following the same logic it is possible to say that stock returns are influenced by energy efficiency and energy input through the output.

This research takes the model with the first specification of technology of BER 95 as the basis and modifies the fixed-coefficient energy-production relationship proposed by the authors to let it vary throughout the sample period based on available energy intensity measures. This step is necessary to make the model reflect the real dynamics of the energy-production interrelation.

2.1.3. Production function and Entropy

After having proved the theoretical linkage between energy efficiency, energy input and stock returns, now the task is to include a measure of CO2 emissions in the abovementioned production function.

The necessity to do so is dictated by extended environmental regulations (e.g. the Kyoto Protocol (2005-2012) and the subsequent Paris Agreement (since 2016)) which consider the negative externalities of the production process (emissions) that are costly for the society and force the firms to internalise this cost in their production functions.

Taking a step back, it is important to bring out on the surface the problem of entropy which was once completely neglected by the Neoclassical economists. According to the Entropy Law (Georgescu-Roegen, 1971) based on the Second Law of Thermodynamics, the output of any economic process is necessarily accompanied by the production of entropy, which can assume the form of heat currents and particle currents (waste, greenhouses gasses etc.). Any kind of use/consumption of an input during the production process produces entropy as a negative externality and it does so at the moment of consumption. Naturally, according to the laws of Thermodynamics, the bigger is the entropy product, the smaller is the quantity of produced useful output, given the same quantity of energy injected in the production process. Then, this phenomenon should be accounted for during the economic modelling. Nonetheless, production functions rarely include waste mostly because it complicates the whole setting and makes the econometric estimation of the equation problematic.

The first attempt to present a production function that included waste as the product of entropy was made by Georgescu-Roegen (1971). According to the author's critical thought the representation of the true-to-life production process by means of the neoclassical production function is nearly impossible because of the non-homogeneity of production with respect to time. The classical model assumes the perfect time homogeneity of the production which ensures the stationarity of the data series. However, the inevitable stops of the production activity take place in real life. Therefore, the correct estimation of the production function is almost impossible unless some assumptions are made, and precisely, the assumption of the perfectly efficient just-in-time production process homogeneous with respect to time. And even in this case the neoclassical model is not sufficient to correctly reflect the production process because it does not consider the side-product of the natural resources and their derivatives which are irreversibly degraded when put to use in economic activity. Since energy enters any production process and cannot be substituted, waste is necessarily created whatever inputs are handled. Moreover, the produced waste has a form of a flow proportional to time.

Then, Georgescu-Roegen's flows-funds point homogeneous production function of degree one, already a simplification with respect to a more general functional model illustrated by the author in his book, looks like follows:

$$qt = \Phi(rt, it, mt, wt; Lt, Kt, St, \zeta t, Ht; t) \quad (21)$$

Here the lowercase letters refer to flow elements (q = the output products; r = natural resources; i = materials coming from other production processes; m = maintenance goods and substances; w =

waste), the uppercase letters refer to fund elements (L = Ricardian land, K = capital, H = labour power, ζ = process-fund containing goods at various stages of production process, S = the reserve of final products to meet the eventual excess of demand).

The element “t” (time) is added to make the Φ function homogeneous and of degree one with respect to all the elements considered in the production function. Another way of presenting the same model in a more readable manner is without the time element. Then the function F is just an ordinary point function:

$$q = F(r, i, m, w; L, K, S, \zeta, H) \tag{22}$$

The author also illustrates the elements in which the equation above can be decomposed:

$$q = f(L, K, H) \leq q^* \tag{23}$$

where q* is the product flow of the factory working at maximum capacity

the reserve fund of finished products $S = S(L, K, H)$, *(24)*

the process fund of semi-finished products $\zeta = C(L, K, H)$ *(25)*

The maintenance products flow: $m = m(K, H)$ *(26)*

but also $w_1 = m$ *(27)*

where w_1 is wear-and-tear waste.

The equations involving capital K justify the fact that the intensity of capital usage is dependent on the quantity of the human labour employed.

Equation (27) owes its existence to the Conservation Law of matter and energy that also says that there should be another relation involving only the transformation waste w_2:

$$w_2 = w_2 (L, K, H) \tag{28}$$

it is so because the amount of transformation waste depends on the technical efficiency of the production facility which is the result of the interaction of all three basic funds.

$$q = g[r, i, w_2 (L, K, H)] \quad (29)$$

Therefore, the author claims that in order to have the true and complete picture of the production process in a factory one needs not just one function (22) but seven basic functions (23) – (29), and waste w_2 will be an unavoidable consequence of the production process.

Notwithstanding the deep analysis behind the model presented above, the division of the production process in seven functions makes the empirical analysis extremely complicated and practically unattainable. The estimation requires a merger in a unique production function.

One well-elaborated attempt was computed by Kümmel (2016) who adjusted a capital-labour-energy-creativity model KLEC (Kümmel, Lindenberger, Weiser, 2015). In this model human creativity supports production factors while they operate and interact with each other and, in this setting, reveals efficiency changes made to cope with the entropy and to mitigate the emissions. This extension is justified by the fact that entropy production is closely connected to energy conversion which was proved by the author to be one of the main drivers of economic growth. The output elasticities resulting from KLEC model are much higher for energy than for labour (Kümmel, 2011; Kümmel, Lindenberger, 2014).

Kümmel constructs pollution functions in the following way: he first proofs Georgescu-Roegen's entropy law based on the entropy balance equation and the entropy production density as far as heat and particle current densities and their driving forces are concerned. Then, pollution functions are shaped to design the response of the society to scenarios when emissions reach critical levels. In these situations, some shares of production factors capital, labour and energy must be devoted to emission mitigation. Whereas these parts of production inputs could be employed to produce goods and services if it was not for the mitigation of emissions, the traditional neoclassic (called "conventional" by Kümmel) economy output is reduced.

The author starts with a base model:

$$Y (K, L, E; t) = Y_0 (t) \exp [F (K, L, E)_t] \quad (30)$$

where $Y_0(t)$ is the production function at time t_0, K is capital, L is labour, E is energy. If no efficiency changes occur in the time span $(t – t_0)$, the production function remains Y_0.

Further the author specifies two special forms of (30) - Y_{CDE} and Y_{L1}.

$$Y_{CDE}\ (K, L, E; t) = Y_0(t)\ (\frac{K}{K_0})^{\alpha_0}\ (\frac{L}{L_0})^{\beta_0}\ (\frac{E}{E_0}))^{1-\alpha_0-\beta_0} \tag{31}$$

Is the energy-dependent Cobb-Douglas function (CDE) with the following output elasticities:

$$\alpha = a\ (\frac{\frac{L}{L_0}+\frac{E}{E_0}}{\frac{K}{K_0}}) \qquad \beta = a\ (c\ \frac{\frac{L}{L_0}}{\frac{E}{E_0}} - \frac{\frac{L}{L_0}}{\frac{K}{K_0}}) \qquad \gamma = 1 - a\ \frac{\frac{L}{L_0}}{\frac{K}{K_0}} - ac\ \frac{\frac{L}{L_0}}{\frac{E}{E_0}}$$

where α is the output elasticity of capital, β is the output elasticity of labour, γ is the output elasticity of energy, *a* and *c* are technology parameters: *a* is a capital efficiency measure; *c* measures energy demand when capital stock is fully utilised.

$$Y_{L1}\ (K, L, E; t) = Y_0(t)\ \frac{E}{E_0}\ exp\ [a\ (2 - \frac{\frac{L}{L_0}+\frac{E}{E_0}}{\frac{K}{K_0}}) + ac\ (\frac{\frac{L}{L_0}}{\frac{E}{E_0}} - 1)] \tag{32}$$

The final model is of LinEx form, so all members depend *linearly* on energy and *exponentially* on factor quotients. Here the output elasticities are affected jointly by pollution functions. The author illustrates this interaction in a “polluted” growth equation. The technology parameters become time-dependent when human creativity is in action. So, in the growth equation the output elasticities of capital, labour and energy inputs are multiplied by the product of pollution functions and technology parameters. In this manner it is clear which is the society’s reaction to pollution critical limits in terms of emissions abatement.

The second method of estimating the impact of emissions mitigation on economic growth proposed by the author is by subtracting the monetary values of goods and services, that could be produced by the shares of production factors dedicated to emissions reduction, from the total production output.

So, the first method produces the final result in units of production, whereas the second method operates in monetary values.

Therefore, Kümmel considers both possible ways of how pollution could enter the production function and affect the production output: in the first instance, by producing the cumulative impact on the output elasticities of production factors, hence, on the right-hand side of the production function; and in the second instance, by taking into account the dual output, the desired and the undesired one, in monetary terms on the left-hand side of the production function.

Despite Kümmel's model being very detailed and functional, it requires large up-to-date datasets on total output, capital, labour, and energy as well as deep knowledge of emissions reducing technologies. Therefore, the econometric analysis is difficult to carry out if no simplifications are applied.

One way to arrive to a manageable equation is to consider only the right-hand side of the production function and to start with a simple Cobb-Douglas production function as in Shadbegian & Gray (2005). In this paper the authors include pollution abatement expenditures in the production function separately from the production factors:

$$Y = f(X, O) \tag{33}$$

Where Y is the output; X is a vector of inputs that includes labour, capital and materials which contain energy; O is a vector of other factors which influence the output, such as the operating costs of pollution reduction (e.g. the worked hours of the special workers who monitor the pollution reduction equipment) or macroeconomic shocks.

In particular, the authors also present an additional formula:

$$Y = f(X_P, X_A, O) \tag{34}$$

Where X_P is a vector of productive inputs; X_A is a vector of emissions abatement inputs (special pollution reduction equipment, etc.). The authors argue that the division of inputs in two groups is necessary to avoid the productivity[7] "mismeasurement". If all the quantities of the inputs are taken as productive, then the real productivity of factors is understated since the emissions abatement inputs do not produce any measured (desired) output and could influence the overall productivity, if ever, only through the negative impact on the productivity of other inputs.

The two types of OLS regressions that the authors perform present the following division: the first type studies the impact of inputs (capital, labour, materials) – productive and pollution abatement versions included separately – on the overall productivity of the plants (US paper, oil, steel sectors), while the second type considers only the productive version of the inputs and the overall pollution abatement operating costs variable. The resulting coefficient of determination is the same for both types of regressions relative to each industrial sector meaning that the pollution reduction operating costs variable includes the impact of all emissions reduction inputs for that sector. The regression output shows that this overall variable has a negative coefficient in all the regressions, whereas the pollution abatement materials variable (includes energy) is negative in paper and steel sectors regressions and positive in oil sector regression, the pollution abatement capital is negative in oil and paper sectors regressions and positive in paper sector regression, the pollution abatement labour is negative in oil sector regression and positive in paper and steel sectors regressions.

However, if we consider only the working capital (measured by the energy input), according to the previously mentioned simplifications, the division between productive and emissive parts of the input is complex to obtain and is not the task of this study. For simplicity this study assumes that the entire quantity of consumed energy produces both the desired output and CO_2 emissions. Therefore, only the first version of the formula by Shadbegian & Gray is applicable to the present analysis.

$$Y = f(X_E, O) \tag{35}$$

Where X_E (or simply E) is the whole energy input, and O is the product of the unitary cost of emissions reduction imposed by environmental regulation (and determined on the special emissions permits market) and the quantity of CO_2 produced by the energy which was used in the production process. This cost is comparable to Shadbegian & Gray's operating cost of reducing pollution and, consequently, should have the same impact on the productivity of the firm.

Apart from the pollution abatement operating costs, Shadbegian & Gray also introduce a CIPP ("change-in-production-process") variable which indicates if a certain plant invested in new more efficient equipment or adopted new production techniques compared with the median share of other

[7] The productivity is calculated as the ratio of the output to inputs.

plants of the same industrial sector. This variable is used by the authors both as a single dummy and in interaction with the pollution abatement capital and pollution abatement operating costs.

The logics suggests that CIPP or its approximations could also be used in the present study: the inverse of the ratio of the energy consumption over the value added at the exchange rate (euro 2015) and the intensity of the consumed energy per ton of output – reflect the interaction with the energy input. The inverse of the energy intensity in terms of value added represents the increase in the value added of the production due to the consumed energy. The inverse of the intensity of CO_2 emissions per ton of output multiplied by the intensity of the consumed energy per ton of output and by the abovementioned ratio of the value added over the energy consumption – show the interaction with the CO_2 emissions reduction operating costs represented by the decreased value added of the production due to the application of the proportional carbon tax.

So, unless there is multicollinearity between energy efficiency measures, all the intensities have the right to enter the production function which considers the value added of the production and not simply the produced quantity.

Therefore, multicollinearity permitting, the estimation would consider the regression of the following log-linear Cobb-Douglas production function:

$$Y = \beta_0 + \beta_1 EC + \beta_2 EnInt + \beta_3 UConsE + \beta_4 CO2 + \varepsilon \qquad (36)$$

Where EC is the electricity consumption input, EnInt is the inverse of the Energy intensity of the relative industrial sector over the value added of the production, UConsE is the Intensity of Electricity Consumption of the relative industrial sector per ton of production, CO_2 is the inverse of the Intensity of CO2 emissions of the relative industrial sector per ton of production.

As far as the impact on the output is concerned, one may expect the positive influence of the energy input and the energy efficiency measure taken together, and at the same time one should expect a negative impact of the operating costs of the reduction of CO_2 emissions. In fact, Shadbegian & Gray predict and then obtain a negative regression coefficient on the pollution abatement expenditures variable.

To see how a similar production function impacts the market return of a firm, first let's take a closer look at the formula Y = *f*(E; O). On the one hand there is the productive energy input that increases the output, and this impact needs to be maximised, and on the other hand there are operating costs linked to the use of energy input with reference to the production of emissions, and the impact of those on the output is negative, therefore, they need to be minimised. Given the complexity of impacts inside the production function, one should proceed to the analysis by steps.

On the other hand, if from the beginning the aim is to follow Kummel's second approach, that is to find a plausible solution to a production function with two separate outputs (the conventional output and emissions), the way to do so could be to elaborate two linear equations relative to two processes which take place simultaneously, convert the outputs in monetary values and then perform the subtraction.

For this purpose, it is possible to use a system of equations by Santetti, Marquetti, Morrone (2018) who explicitly stated the existence of desired and undesired products of any capital-labour-energy production process and presented two Leontief production functions: the first being a standard capital-labour-energy production function and the second being a pollution function involving the same inputs of the first function:

$$Y = \min(\rho K, xN, eE) \tag{37}$$

$$P = \min(aK, bN, cE) \tag{38}$$

Where Y is the desired output or GDP in 1995 reais, P is waste (CO2 emissions in tons), K is net capital stock of fixed assets in 1995 reais, N is labour (number of workers), E is energy supply (TOE, tons of oil equivalent). In the equations (37) and (38) the coefficients differ to distinguish the relative elasticities of the output (desired or undesired) on each of the inputs. The units of measure are the following: x=Y/N in 1995 reais per worker; ρ=Y/K is a number; e=Y/E in 1995 reais per TOE. a=P/K in tons of CO2 per 1995 reais; b=P/N in tons of CO2 per worker; c=P/E in tons of CO2 per TOE. o=Y/P in 1995 reais per ton of CO2. The parameters (x, ρ, e) are referred to as technical variables, while (a, b, c) are emissions-intensity measures. Both groups of parameters together define the production technique of a certain production process at a given point in time.

In that article Santetti, Marquetti and Morrone elaborated on the existing the theory of production with greenhouse gas emissions by Foley, Michl (1st edition 1999) & Tavani (2nd edition 2019). The scheme that the latter authors used for the representation of the production process based on burning fossil-fuels is the following:

$$\boxed{\begin{gathered} 1 \text{ labor} + k^{FF} \text{ capital} \rightarrow \\ x \text{ output} + (1 - \delta - D(CD))k^{FF} \text{ capital} + x\ \mathrm{CO_2} \end{gathered}}$$

Source: Foley, Michl, Tavani (2019), p. 354.

Where $\boldsymbol{k^{FF}}$ is fossil-fuel technology capital intensity, $\boldsymbol{\delta + D(CD)}$ is the capital depreciation rate which includes the depreciation rate per unit of capital $\boldsymbol{\delta}$ and the damage function $\boldsymbol{D(CD)}$ representing the capital loss due to the climate change when the atmospheric concentration of CO2 is CD. Here the authors assume that there is no scarcity of the reserves of fossil fuels[8] and that the climate damage manifests itself in the destruction of means of production, and, hence, in the increase of the capital depreciation rate. For the sake of simplicity, the authors assumed that to produce X units of output X units of CO2 need to be emitted. So, the unit of measurement for CO2 is the amount of CO2 emitted while producing one unit of output.

At the end of the period the (fossil-fuel) production technique of a productive process gives birth to three results:

1) X units of new output;
2) the capital depreciated by the factor $(1 – \delta – D(CD))$;
3) X units of CO2 emissions.

This scheme is representative of the production process at any given moment. However, if one should represent the production process which lasts in time, then the depreciated capital should not be considered as one of the outputs because it enters the production process as the input in the following moment. Therefore, only the production output and the emissions remain as the result of the production process.

Next, a simplified model along the lines of Santetti, Marquetti, Morrone (2018) will be presented in order to link conceptually energy inputs and CO2 emissions to stock market returns, which is the task of this work.

2.1.4. Production-based model with CO2 emissions.

Inspired by the idea by Kümmel that energy is the driving force of economic growth, to model the production process of industrial sectors I consider a simplified version of Santetti, Marquetti, Morrone (2018), without taking into consideration the labour power, thus assuming no scarcity of this input. Then the model for the desired output will look like follows:

$$Y = min\ (\rho K, eE) \qquad (39)$$

[8] Otherwise, it would be possible to burn all the reserves of fossil fuels on Earth causing a climate catastrophe.

Where symbols and coefficients are as in Santetti, Marquetti, Morrone. Therefore, the coefficient *e* is regarded as the inverse of energy intensity (or “the productivity of energy” as the authors put it), the state of linear technology or the energy efficiency. Following Kümmel, it is logical to think that this coefficient increases as time passes due to the technology improvement, so it can be represented as *e(t)*. Also, by making another simplification and regarding capital as an input which is not subject to scarcity, the production function will become:

$$Y(t) = e(t)\,E(t) \qquad (40)$$

Where *e(t)* is naturally the energy efficiency (the inverse of energy intensity) and is calculated as

$$\frac{Y(t)}{E(t)}$$

The evidence of the direct relationship between the production output and the energy input is given by the comparison of the trend of the Italian production index (IPI) with that of the IMCEI (*Indice mensile dei Consumi Elettrici Industriali*), the industrial electricity consumption index elaborated monthly by Terna. The correlation between the two series is particularly high (ranging from 0,90 - base year 2010, to 0,95 - base year 2015). The figures below provide the visual analysis relative to the sample January 2011 – December 2017 with the base year 2010 (average 2010=100) and for the sample January 2016 – May 2020 with the base year 2015 (average 2015=100).

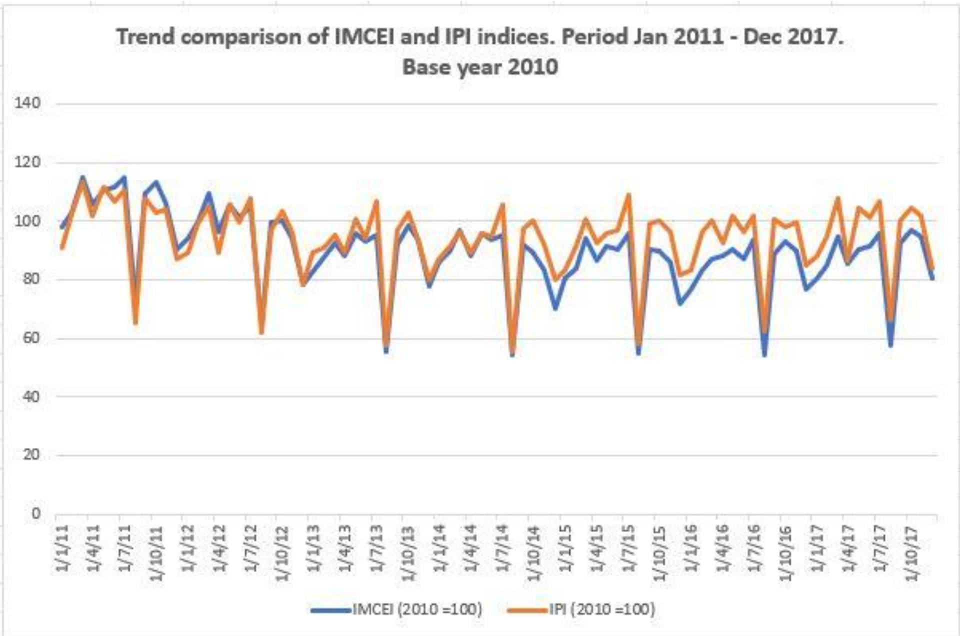


Figure 5 *The trend comparison of IMCEI, the monthly industrial electricity consumption index, and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2010=100). The orange line refers to the IPI index, the blue line refers to the IMCEI index. Sample period January 2011 – December 2017.*

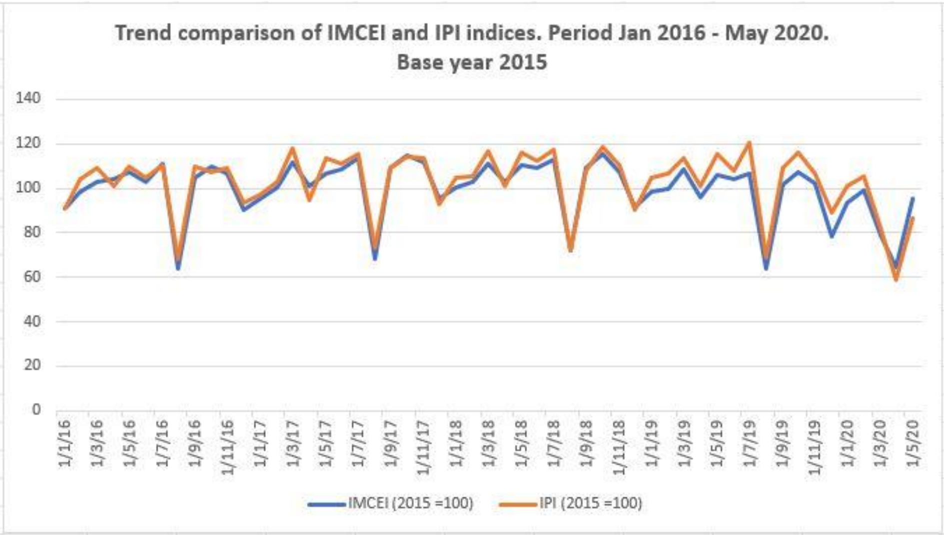


Figure 6 *The trend comparison of IMCEI, the monthly industrial electricity consumption index, and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2015=100). The orange line refers to the IPI index, the blue line refers to the IMCEI index. Sample period January 2016 – May 2020. Monthly data.*

The figures above empirically prove the existence of the direct relationship between the production output and the energy input as hypothesised theoretically by equation (40). As it is put on display by Figure 6, the indices sometimes perfectly overlap due to almost perfect positive correlation between the series.

Appendix A provides a comparative analysis of some of the components of IMCEI, the electricity consumption series relative to four energy intensive industrial sectors (Steel, Non-ferrous Metals, Cement and Chemicals), with the IPI index for both base years. The results confirm the trend shown in Figure 5 and Figure 6, mainly that the industrial electricity consumption tracks the industrial production over time.

As for the pollution (CO2) production function, one can make the same simplifications and start with a model including only capital and energy:

$$P = \min(aK, cE) \qquad (41)$$

Where the coefficient *c* is the CO2 emissions intensity (CO2 emissions per unit of energy input $\frac{P(t)}{E(t)}$) which is time-variable (*c = c(t)*) by Kümmel's idea.

And the simplification without capital:

P(t) = c(t) E(t) *(42)*

Moreover, the coefficients *e(t)* and *c(t)* are negatively correlated: the higher is the energy efficiency of the production process, the lower are the CO2 emissions per unit of used energy. On the other hand, energy intensity 1/*e(t)* and *c(t)* should be positively correlated. This idea is empirically checked in Table 20 later in the Methodology section. Because production is directly proportional to energy used, we also have that the higher is the energy efficiency, the lower are the CO2 emissions per unit of output (*δ(t)*), meaning that *δ(t)* is a decreasing function of *e(t)*. Then the CO2 emissions per unit of production is also negatively correlated with the energy efficiency measure. Under the special case when $\delta(t) = \frac{\mu}{e(t)}$ where μ > 0 is a constant, the product *δ(t) e(t)* is a constant, μ, and the logarithm of *δ(t)* is perfectly (negatively) correlated over time with the logarithm of *e(t)*.

As far as *Y(t)* and *P(t)* are produced simultaneously with the same energy input but different negatively correlated coefficients, two models working simultaneously need to be analysed.

Let's take an energy intensive production, for example, a steel company with the usual production function Y = max(K, N, E) and no constraint on labour and capital as before. It produces one good *x* and operates in two periods of time t_0 and t_1 with linear technology. The usual problem (foc) that the firm needs to solve is then as follows:

$$\max_{\varepsilon} E_t[x_t + P_x \tilde{x}_{t+1}] \tag{43}$$

$$\text{s.t.} \quad x_t = e_t\,(\Psi - \varepsilon)$$

$$\tilde{x}_{t+1} = \tilde{e}_{t+1}\,\varepsilon$$

Where x_t is the product at time *t*, $\tilde{x}_{t+1}$ is the product at time *(t+1)*, e_t is the energy efficiency (production per unit of consumed energy) at time *t*, $\tilde{e}_{t+1}$ is the energy efficiency at time *(t+1)*, P_x is the price at *t* of one unit of product that will be available at *(t+1)*, Ψ is the total quantity of energy at *t*, *ε* is the part of energy whose consumption is postponed to *(t+1)*, *t* is the numeraire.

The maximization problem can also be rewritten in terms of R, the cost of capital needed to discount the future production. As far as $R = \frac{1}{P_x}$, then:

$$\max_{\varepsilon} x_t + \frac{E_t[\tilde{x}_{t+1}]}{R} \tag{44}$$

$$\text{s.t.} \quad x_t = e_t\,(\Psi - \varepsilon)$$

$$\tilde{x}_{t+1} = \tilde{e}_{t+1}\,\varepsilon$$

After solving the problem above, we get: $R = \frac{E_t[\,\tilde{e}_{t+1}]}{e_t}$

Recalling the formula for the pricing kernel for the consumption-based asset pricing $\left(m = \beta\,\frac{u'(C_{t1})}{u'(C_{t0})}\right)$ which linked m to the marginal rates of substitution, an analogous formula for the production-based setting which ties the pricing kernel (the discount factor) to the marginal rates of transformation would result in:

$m = \frac{\tilde{e}_{t+1}}{e_t}$ given linear and deterministic technology.

Here the firm may postpone the consumption of a part of the available energy without facing any cost. In reality it is not quite so, as securing energy availability in a future period, either by way of storage or securing delivery of newly produced energy through the forward market, is costly. Therefore, a price of shifting the energy to the next period (P_ε) needs to be introduced. This cost is not fixed, it depends on the quantity of energy that needs to be stored/acquired to be consumed in the future. If storage of unused energy ε is implemented at the level of the individual firm, the cost will be a function $P_\varepsilon(\varepsilon)$. Under the assumption of some economy of scale in the storage of energy, $P_\varepsilon(\varepsilon)$ could be a convex decreasing function in ε[9]. However, more realistically, P_ε is set outside the firm's control in the energy production system through the presence of aggregate storage facilities, and the structure of the energy production industry which determines a price for future delivery.

$$\max_{\varepsilon}\; x_t + \frac{E_t\,[\tilde{x}_{t+1}]}{R} \tag{45}$$

$$\text{s.t.} \quad x_t = e_t\,(\Psi - P_\varepsilon\,\varepsilon)$$

$$\tilde{x}_{t+1} = \tilde{e}_{t+1}\,\varepsilon$$

The cost of capital is then equal to $R_x = \frac{1}{P_\varepsilon}\,\frac{E_t[\,\tilde{e}_{t+1}]}{e_t}$ where $R^\varepsilon = \frac{1}{P_\varepsilon}$ may be defined as the return on the shift of energy to the future. It can be obtained on the Forward Electricity Market (MTE). However, the value is in nominal terms, so R^ε should be adjusted for inflation (*I*). Then the cost of capital formula will become as follows:

[9] In this case the first order condition would involve the derivative with respect to ε of the product $P_\varepsilon(\varepsilon)\,\varepsilon$.

$$R^{m} = R^{\varepsilon}(1+I)\,\frac{E_t[\,\tilde{e}_{t+1}]}{e_t} \tag{46}$$

where R^{m} is the return on the energy market. The formula shows that R^{m} is directly influenced by the change in energy efficiency of the firms operating on the energy market ($\frac{E_t[\,\tilde{e}_{t+1}]}{e_t}$). So, according to this simplified model (no labour costs, no depreciation of capital since there is only the working capital, no other production costs) the firm maximises its production by considering only the real return on the energy (electricity) market, which includes the forward energy price and inflation, and the technical progress of the relative industrial sector expressed by the energy efficiency measures. And since production is closely related to stock prices, then these variables will be used further in the equation explaining sector stock returns.

As in this simple model, where production is only based on the energy input and the intensity of CO2 emissions is negatively correlated with the energy efficiency, there will be a physical incentive in the economy to improve energy efficiency over time as this improves output given the energy input, and as consequence there will be a decrease of CO2 emissions. This dynamic element is not explicitly present in the theoretical model. If other inputs were considered, there could also be a possible negative effect on the CO2 emissions from the overall productivity of the firm through the negative impact on the productivity of other inputs (e.g. global warming affecting the productivity of the labour force and the productivity of fixed capital by leading to a faster wear of the machinery). The present simplified version of the production function does not account for these issues. However, the CO2 coefficient $\delta(t)$ will provide useful information on technology and productivity.

2.1.5. Pollution as a cost for the firm.

The regulatory framework for polluting industries of the Euro zone imposes a cost on polluting firm proportional to the CO2 emissions, the so-called carbon tax. Some European countries, for example Sweden, achieved a significant reduction of CO2 emissions thanks to the carbon tax introduced in the 90s. Other countries like Italy have never made the application of the carbon tax effective until now but have relied on the market for greenhouse emissions permits ETS (EU Emissions Trading System). The reason for the existence of carbon permits' trading lies in the fact that each polluting firm is given a certain number of free carbon permits that correspond to the level of emissions considered desirable for this firm on the basis of a series of criteria (industrial sector, size, the risk of relocation in zones with less environmental pressure etc.). At the end of each year these permits need to be given away in the adequate quantity to cover all the CO2 emissions of that year. If the permits are more than needed, they can be kept by the firm for the future use or traded at ETS. If the permits are less than needed, they can be acquired at ETS.

If P_b is the price for future emissions at time *t*: it is the price of greenhouse emissions permits that are traded at ETS. These "carbon permits" can be kept by the firm to cover its future emissions, therefore, P_b is the price that the firm pays today to cover its emissions that will be generated by the future energy consumption.

So, the firm is not only interested in maximising the production of product *x* but also in minimising its greenhouse emissions which are costly for the firm due to the more and more stringent environmental regulation.

In the short term the firm will not be able to alter the available production technology towards increased energy efficiency, so there is limited scope for minimising emissions. Still the cost can be considered in the firm's objective function.

A way to take this cost into account is to construct a pollution production function and solve the minimisation problem, and then derive the net return on the use of the working capital using the result of that minimisation. Yet another way is to imagine it related to the amount of production output through a function $\tau(\delta_t)$[10]. Both methods show that, apart from the forward energy price and inflation, the intensity of CO2 emissions is relevant for the firm's productivity. Therefore, the intensity of CO2

[10] Together with the production of product ***x*** a certain quantity of CO2 (***b***) is emitted in the atmosphere. Then, an additional problem arises due to the pollution production function B = min (K, N, E) with no constraint on labour and capital as before:

$$\begin{aligned} &\min_{\varepsilon} E_t[b_t + P_b \tilde{b}_{t+1}] \\ \text{s.t.} \quad & b_t = \delta_t\ (\Psi - P_\varepsilon\ \boldsymbol{\varepsilon}) \\ & \tilde{b}_{t+1} = \tilde{\delta}_{t+1}\ \boldsymbol{\varepsilon} \end{aligned} \tag{47}$$

where $\boldsymbol{\delta}$ is the intensity of the emissions of CO_2 for one unit of energy and P_b is the price for future emissions at time *t*. The solution gives: the cost of emissions $R_b = \frac{1}{P_\varepsilon}\frac{E_t[\tilde{\delta}_{t+1}]}{\delta_t}$ where $R^\varepsilon = \frac{1}{P_\varepsilon}$ is the return on the shift of energy to the future. After the adjustment for inflation: $R^c = R^e(1+I)\frac{E_t[\tilde{\delta}_{t+1}]}{\delta_t}$ where R^c is the cost of greenhouse emissions due to electricity usage which increases if the intensity of CO2 emissions for one unit of energy $(\frac{E_t[\tilde{\delta}_{t+1}]}{\delta_t})$ increases. Then, the net return on the use of the working capital R^N can be obtained by subtracting R^c from the overall gross return R^m on the energy market.

Another way to face the problem of the CO2 emissions cost is to link it directly to the production output through a function $(1-\tau(\delta_t))$ that decreases the value of the firm:

$$\begin{aligned} &\max_{\varepsilon} E_t[x_t(1-\tau(\delta_t)) + P_x\tilde{x}_{t+1}(1-\tau(\delta_{t+1})) \\ \textit{s.t.} \quad & x_t = e_t\ (\Psi - P_\varepsilon\ \varepsilon) \\ & \tilde{x}_{t+1} = \tilde{e}_{t+1}\ \varepsilon \end{aligned} \tag{48}$$

The solution will give: $R^m = R^\varepsilon(1+I)\frac{(1-\tau(\delta_{t+1}))}{(1-\tau(\delta_t))}\frac{E_t[\tilde{e}_{t+1}]}{e_t}$ (49)

emissions should be included in the equation defining stock returns.

Summing up the results obtained hereabove and considering the theoretical model of simultaneous production of desirable and undesirable output according to equations (40) and (42) and, in particular, the linkage between this dual output and the overall firm's productivity impacting the relative stock price, it is reasonable to include in the stock returns equation under estimation the following variables: the electric energy consumption, energy efficiency measures and the intensity of greenhouse gasses emissions, the forward price of electric energy, the price of carbon permits and the inflation index. As far as the price change of carbon permits is concerned, it is added to the model to act like a control variable. It is not essential in the elaborated economic model which is based on the firm's incentive to improve its energy efficiency for productivity reasons, regardless of the legislation that penalises greenhouse emissions. However, it was included among other regressors to double check the inference results. As for the inflation index, it conveys little information if included in the regression as one of the predictors. The only conclusion which can be made is the one deducted from how fast stock prices usually react to the changes in inflation during a certain period. It is well known that the correction for inflation of stock returns occurs rather slowly if inflation grows according to the expectations. Therefore, I get rid of inflation by subtracting it from the stock returns and obtain the real rate of stock return not subject to inflation fluctuations. The formula which is usually used for this purpose is Real Rate of Return = (1+Stock Return)/(1+Inflation) -1. Then the equation to be tested would become:

$$RRR_x = \beta_0 + \beta_1 \Delta EC + \beta_2 EnInt + \beta_3 UConsE + \beta_4 CO2 + \beta_5 \Delta P_E + \beta_6 \Delta P_{CO2} + \varepsilon \qquad (50)$$

Where RRR is the real rate of stock return calculated as specified above. It is expressed as the year-over-year, or the month-over-month change in stock prices adjusted for inflation.

This model is along the lines of Chen, Roll and Ross (1986) to the extent that the explanatory variables which are related to the mechanism generating returns according to the simplified model equation (50) are tested.

The explanatory variables considered are the:

ΔEC **–** the sector electricity consumption, expressed as the year-over-year or the month-over-month seasonally adjusted percentage change.

EnInt **–** the sector value-added energy intensity expressed as the total consumed energy per value added to production in 2015 Euro. Monthly temporally disaggregated data from annual data.

UConsE – the sector physical energy intensity expressed as the consumed energy per ton of output product (only for the Cement sector this variable is the electricity intensity and not the total energy intensity as for the other sectors). Monthly temporally disaggregated data from annual data.

CO2 – the sector CO2 emissions intensity expressed as the quantity of emitted CO2 per ton of output product (only for the Chemicals sector this variable is not physical but value-added – calculated as ratio of CO2 emissions per value added to production in 2015 Euro). Monthly temporally disaggregated data from annual data.

$\boldsymbol{\Delta P_E}$ - the forward price of electric energy, expressed as the year-over-year or the month-over-month seasonally adjusted percentage change.

$\boldsymbol{\Delta P_{CO2}}$ - the price of carbon permits, expressed as the year-over-year or the month-over-month seasonally adjusted percentage change.

Before moving to the empirical estimation of the equation (50), it is necessary to dwell on some reflections regarding the theoretical value of the presented model.

First, it is important to underline the fact that the model shown above is the unique attempt to elaborate an easily solvable production function with dual output, the desired and the undesired ones, produced by one input (energy). This idea is based on the concept of the negative environmental externality which accompanies any production process but is usually analysed separately from the impact of other production factors. One difficulty of including this externality in the productive economy consists in fact that the units of measure of the output of the negative externality differ from the units of measure of the traditional output. Another reason why the production function of this dual output form has not been considered before is because generally the producer is more interested in the output which generates revenues and tends to ignore the undesired output (negative externality) which impoverishes the society by damaging the environment. To repair to this disadvantage for the economy the legislator imposed a cost on the producer for the greenhouse gasses emissions. In this way the undesired output of the production process was transformed in a monetary cost for the producer and, thus, gained the right to enter the production function.

The proposed model is undeniably in a simplified form. As in BER 95 the adjustment for labour effort (hours worked) was due but was consciously neglected for the sake of simplicity and feasibility of econometric analysis. The same was done with for the capital input. Besides, as the environmental externality is linked to time, its effects are measured throughout some time spans. In this work I take an instant and model the production function in that instant, considering the momentary production of greenhouse gasses. Even if this fact does not reflect exactly the physical reality of the production process, this simplification is needed to make the explanation of the process clearer. Georgescu-Roegen presented a complex and multi-stage dynamics of the production process which included waste. However, its transformation in a form useful for the empirical estimation would be troublesome if not completely unattainable. Therefore, the simplification was done here, notwithstanding that the deeper analysis of the physics of the production process (meaning the reintroduction of the labour and capital in the production function and the elaboration of multi-staged dynamics) are left for the future research.

Next in order are some considerations on the inner dynamics of the equation (50).

As far as the electricity consumption is concerned, its regression coefficient may vary from one industrial sector to another depending on the overall sector energy efficiency. The normal situation is when electricity consumption (the month-over-month or the year-over-year variation of it) has a **positive** coefficient: according to equation (46) (and other modifications) $R = E(e_{t+1})/e_t$ where e is energy efficiency, hence, the return is positively related to the increase in energy efficiency, or (the energy intensity kept constant) to the decrease in energy input (output kept constant). So, if put in a very simple form: the reduction (increase) in the MoM or YoY variation of EC accompanied by the increase (decrease) in energy efficiency will lead to higher (lower) productivity and production output, higher (lower) stock prices and, thus, lower (higher) stock returns. The abnormal situation may arise when the electricity consumption features a **negative** coefficient: then either the equipment is getting obsolete very fast, and even higher use of electricity (lower MoM or YoY change in EC) cannot improve the productivity which is getting reduced, leading to lower stock prices and, thus, higher stock returns; or the equipment has undergone an improvement and became extremely energy efficient, so that lower electricity usage (higher MoM or YoY change in EC) led to higher output, higher stock prices and, hence, lower stock returns. Each case should be analysed carefully to understand which dynamics takes place.

Another important matter is the statistical significance of the electricity consumption in the regression models when the variable is used alone and in combination with energy efficiency measures. The withdrawals of electricity which are registered by Terna, take account only of the electricity taken by industrial sector from the national grid. It does not consider the energy which the sector may produce by itself (renewable sources of energy like photovoltaics). It also ignores the fact that if the investments in more efficient equipment are not made, the consumption of electricity would inevitably rise without impacting the output. All this information can be deducted from the energy and CO2 emissions intensities. These energy efficiency measures may correct the impact of the electricity consumption on the stock return (**positive** coefficient sign and statistical significance) when sector energy efficiency is relatively low, it may amplify it (**negative** coefficient sign) when the sector energy efficiency is particularly high or may be insignificant in the regressions when the electricity consumption variable is enough to explain the stock returns and energy efficiency measures do not add any other predictor power to the model. So, the functioning of the elaborated simplified model should be valued accurately in each specific case considering the actual interaction of electricity consumption and the variation of energy efficiency of the industrial sectors under analysis.

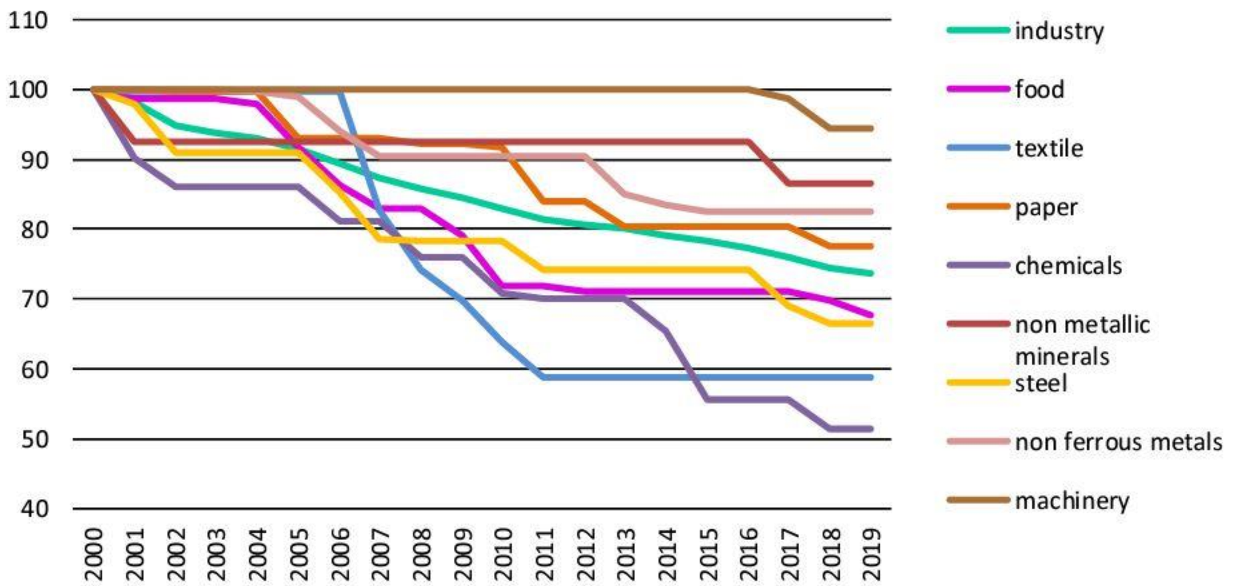
Besides, according to already mentioned positive relationship between energy intensity and CO2 emissions intensity, one should expect the same sign of the regression coefficient for these variables. Speaking of the impact that energy efficiency measures produce on stock returns, it is plausible to anticipate a **positive** regression coefficient on the intensity of CO2 emissions and energy intensities. This is because the increase of energy efficiency is directly linked to the increase in future productivity, and the energy efficiency measures (energy and CO2 emissions intensities per ton or 1€ of output) are inversely related to the energy efficiency. So, an increase in energy efficiency measures means an increase in the quantity of energy used in the production process and an increase of CO2 emissions, keeping the output constant. Then, it is obvious that the energy efficiency of the plant is reduced in this case; the future production is reduced, and the market investors would require an additional risk premium on the relative stock return (Agrawal & Osadchiy, 2022; Hiroki, Iwatsubo, Watkins, 2022 and others). In other words, an increase in the energy and CO2 emissions intensities will mean a reduction of the energy efficiency of the equipment and will bring to a decrease in the productivity and the production output, leading to lower stock prices and, thus, higher stock returns (due to the inverse relationship between stock prices and stock returns). However, some abnormal situations may be encountered when the industrial sector, for example, is big and extremely energy efficient. In that case the increase in energy and CO2 intensities (especially the value-added versions of them) may not lead to the reduction in energy efficiency with the subsequent reduction of productivity but could mean a temporary situation which would be taken care of rapidly by the increase (instead of a reduction) of the scale of highly energy efficient production which would then lead to higher prices and, hence, lower stock returns. So, in this case the regression coefficient of the energy efficiency measures could be negative.

Needless to say, the multicollinearity between the energy efficiency measures is highly probable to arise during the regression analysis. Therefore, the contemporaneous use of all three energy efficiency measures in sectorial regressions is troublesome. In the empirical part of this study, I carefully choose the best performing energy efficiency measure to be used in the regressions for each energy-intensive industrial sector under consideration.

The month-over-month (or year-over-year) change in the energy forward price (forward energy return) and the month-over-month (or year-over-year) change in the price of carbon permits' price (carbon credits return) also impact the productivity of the industrial sectors (Calligaris et al, 2018) and, hence, their stock returns. The normal situation is when an increase in forward energy price and/or in carbon permits' price (the decrease in relative returns) leads to a reduction in output and productivity of the firms and, therefore, the decrease in the relative stock price and, hence, an increase in the stock return. So, for the variables used in their month-over-month and year-over-year form the expected regression coefficient should be **negative**. An abnormal situation may arise when the forward energy price change and/or the carbon permits' price change are insignificant in the regression meaning their zero elasticity with the firm's productivity. This may happen when the industrial sector is capable to improve its energy efficiency rapidly before the impact of the forward energy price change (or the carbon permits' price change) on the productivity becomes visible (for example, by taking advantage of the economies of scale) and/or when it can easily transfer the increase in production costs to the intermediate and final consumer of the finished product. Then the industrial production of that sector would not feel any impact from the increase in the forward energy price and/or in the carbon permits' price. There can be cases when the sign of the regression coefficient of the carbon permits' price change is different from that of the forward energy price change. One of these cases is when the industrial sector under consideration is highly sensitive to the change in carbon price: then it makes structural changes to its production line, or it reduces its energy intensity almost immediately after having learnt the news. Another case may arise when the industrial sector is big enough to minimise the impact of the increased cost by upscaling the production and/or increasing the prices at which the product is sold to the intermediate/final consumers. If the upscaling is larger than needed to minimise the cost, than the impact on stock returns of the increase of carbon prices would be reversed.

So, the matter of signs and the magnitude of the coefficients for any predictor depends largely on the energy efficiency of the industrial sectors under consideration and the correlation between the regressors.

The following graph shows the energy efficiency index in Italian industry for the period 2000-2019, year 2000 taken as the base. Lower values mean higher energy efficiency. These data should be combined with the data on sector energy consumption (see Figure 16).



Source: Odyssee

Figure 7 *Energy Efficiency Index in Italian Industry (2000=100). The energy efficiency of industry measured by ODEX index, elaborated by Odyssee Project, based on the data provided by ENEA, National Agency for Energy Efficiency, mainly the energy efficiency measures (energy/electricity and CO2 emissions intensities). The decreases in the value of ODEX mean the increases of the energy efficiency of the industrial sectors. Sample period 2000-2019.*

It is clear from the figure above that the Italian Chemicals sector improved its energy efficiency greatly in the recent years. The Steel sector also reports a significant improvement, even if less marked compared to the Chemicals sector. But the Construction & Materials sector (Non-Metallic Minerals in the graph above) does not show extraordinary results from the point of view of energy efficiency. The energy efficiency index almost hasn't changed for this sector during the past 20 years. Therefore, it is reasonable to expect different regression results for these sectors.

The next section explains in detail the procedure of the regression analysis and presents the relative results.

2.2. Data and Methodology.

2.2.1. Data.

Industrial energy consumption historical data (Gwh) for the period between 2010 and 2020 (January 2010 – May 2020) were kindly provided by Terna. The data are monthly electric energy supply statistics (GWh) referring to four energy-intensive Italian industrial sectors (Cement, limestone, plaster; Chemicals; Non-ferrous Metals; Steel). The list of the Italian companies whose electricity consumption is considered by Terna, is not available. The raw industrial electricity consumption time-series provided by Terna are affected by seasonality which could bias the inference results (reduced degrees of freedom due to spurious correlations between independent variables). Therefore, following the guidelines by Terna, the raw data were first tested for seasonality and then adjusted for it by the Demetra+[11] software, and thus, only the seasonally adjusted time-series were used in all the steps of the research.

The time-series of price indices that constitute the dependent variables in the statistical tests (Italian stock returns) were downloaded from the website www.investing.com. The stock market indices were associated with the industrial sector electricity consumption provided by Terna in the following way:

Table 14 : *Matching of Stock Market Indices to Industrial Electricity Consumption by sector*

Stock Market Index	Sector Electricity Consumption
Ftse Italia All Share Basic Resources	Steel Non-Ferrous Metals
Ftse Italia All Share Construction & Materials	Cement, Limestone and Plaster

[11] The TRAMO-SEATS procedure is applied by following the example by Terna for the seasonal adjustment of the monthly raw data for demand of electricity. This procedure is also recommended by the "EES Guidelines for seasonal adjustment". Its main purpose is to isolate and estimate calendar and temperature effects, and the impact of the seasonal and trend-cycle components on monthly data. The procedure applied to a time-series consists in two steps: model identification and model testing.
1) the TRAMO procedure determines an appropriate ARIMA model (identified either automatically or set by the user), both for the non-seasonal and the seasonal part.
2) the SEATS procedure separates the series in trend-cycle component, the seasonal component, and the stochastic part by means of the spectral analysis applied to the linearised time series through the application of logarithms. The trend-cycle component includes the long-term behaviour of the analysed data (trend) and the deviations of the observations from the trend (cycle). The seasonal component is calculated subtracting the trend-cycle component from the time-series. The peaks of the spectrum are then the seasonal component of the series. The erratic component is white noise.
The procedure then determines series-specific weighting coefficients and uses them to produce the final seasonally adjusted time-series.

Ftse Italia All Share Chemicals	Chemicals

Table 15: *Descriptive Statistics (investing.com)*

The table gives a detailed descriptive statistics of the data downloaded from the website investing.com

Index Name	Code	Stock Exchange	Currency	Time Frame	Period	Price Type
Ftse Italia All Share Basic Resources	FTITLMS5510	Milan	Euro	Monthly	Dec 2009 – Sept 2021	Last Price avg
Ftse Italia All Share Construction & Materials	FTITLMS5010	Milan	Euro	Monthly	Dec 2009 – Sept 2021	Last Price avg
Ftse Italia All Share Chemicals	FTITLMS5520	Milan	Euro	Monthly	Dec 2009 – Sept 2021	Last Price avg

A time varying energy intensity, or energy efficiency, is included in the model[12]. All the necessary energy-efficiency measures were downloaded from Odyssee Mure project website[13]. And specifically: the Primary Metals (ISIC 24) Energy Intensity at constant price (koe/EUR2015); the Intensity of CO2 emissions of the Steel industry (tCO2/t); the Specific Energy consumption of the Steel industry (toe/t); the Non-Metallic Minerals (ISIC 23) Energy Intensity at constant price (koe/EUR2015); the Intensity of CO2 emissions of the Cement industry (electricity included) (tCO2/t); the Specific Electricity consumption of the Cement industry (kWh/t); the Chemical Industry (ISIC 20-21) value-added Energy Intensity at constant price (koe/EUR2015); the value-added total CO2 Intensity of the Chemical industry (kCO2/ EUR2015). All the energy-efficiency data are at annual level. The details on the calculations of the abovementioned ratios are given in the table below.

[12] In the recent years all the energy intensity measures seem to have a decreasing trend which testify to the fact that the energy efficiency is improving in all the industrial sectors. The inclusion of these measures in the model corrects the energy consumption data where necessary and puts the focus on the real impact that the latter have on the productivity of the firms and, therefore, on the stock prices.

[13] https://www.odyssee-mure.eu/ A project supported by H2020 programme of the European Commission which monitors energy consumption, efficiency trends and energy efficiency policy measures by sector for EU countries, Norway, Serbia, Switzerland, and the UK.

Table 16: Description of the Calculation of Energy Efficiency Measures (Odyssee – Mure database)

Energy Efficiency Measure	Calculation
Energy intensity of Primary Metals (at exchange rate)	The ratio between the final energy consumption and the value added at constant price (koe/EUR2015)
Total CO2 emissions of Steel per ton (included electricity)	The ratio between total CO2 emissions and total Steel production measured in tons (tCO2/t)
Unit consumption of crude Steel	The ratio between the energy consumption of the Steel industry and the steel production measured in tons (toe/t)
Energy intensity of Non-metallic Minerals (at exchange rate)	The ratio between the final energy consumption and the value added at constant price (koe/EUR2015).
Total CO2 emissions of Cement per ton (included electricity)	The ratio between total CO2 emissions and total Cement production measured in tons (tCO2/t)
Unit consumption of electricity of Cement	The ratio between the electricity consumption of the Cement industry and the Cement production measured in tons (kWh/t).
Energy intensity of Chemicals (at exchange rate)	The ratio between the final energy consumption and the value added at constant price (koe/EUR2015)
Total CO2 intensity of Chemicals (included electricity)	The ratio between total CO2 emissions and total Chemicals production measured in EUR2015 (kCO2/EUR2015)

The table gives the official definition of the energy efficiency measures (column on the left) and the detail on their calculation (column on the right).

Source: Odyssee-Mure

As soon as the energy efficiency data are available only at annual level, the monthly time series had to be produced artificially. Denton[14] procedure in Stata software was used for this purpose, using as the indicator time series monthly energy prices (PUN, Prezzo Unico Nazionale) downloaded from the official website of the Italian energy market (www.mercatoelettrico.org). The table below shows the correlations between energy efficiency measures and the energy price in Italy. The values are

[14] Denton procedure (Denton, 1971), a univariate method of temporal disaggregation with indicators. For the conversion of low frequency data into high frequency data, this approach considers an indicator series, available at high frequency, which is correlated with the original time series, and then fills in the latter's missing high frequency values according to the movements of the indicator series. It minimises the sum of squares of the deviations between the indicator and the resulting series (can be done on levels, first differences or second differences).

positive and reasonably high for the PUN time series be considered the indicator for the Denton temporal disaggregation method.

Table 17: *Correlation between energy and CO2 emissions intensities and the Italian energy price (PUN)*

	Energy efficiency measures							
	Energy intensity of Primary Metals (koe/EUR2015)	Unit consumption of crude steel (toe/t)	Total CO2 emissions of steel per ton (tCO2/t)	Energy intensity of non-metallic minerals (koe/EUR2015)	Unit consumption of electricity of Cement (kWh/t)	Total CO2 emissions of cement per ton (tCO2/t)	Energy intensity of Chemicals (koe/EUR2015)	Total CO2 intensity of Chemicals (kCO2/EUR2015)
PUN (€/MWh)	0,66	0,57	0,70	0,29	0,40	0,50	0,65	0,69

Temporal disaggregation methods, such as the Denton method (Denton, 1971), are widely used in official statistics to obtain high-frequency estimates of key economic indicators (Sax & Steiner, 2013 among others). The necessity to convert low frequency energy efficiency measures into high frequency series in this research was dictated by the fact that they had to be used in combination with the energy consumption series which was available at monthly level. Its use at annual level would have led to information loss. Besides, the decision to perform tests only with annual data would further restrict the available data set which is not particularly large.

The energy efficiency measures were associated with the industrial sector electricity consumption provided by Terna in the following way:

Table 18: *Matching of Energy Efficiency Measures to Industrial Electricity Consumption by sector*

Energy Efficiency Measure	Sector Electricity Consumption
Primary Metals (ISIC 24) Energy Intensity CO2 emissions of Steel per ton Unit Energy consumption of Steel	Steel Non-Ferrous Metals
Non-Metallic Mineral (ISIC 23) Energy Intensity CO2 emissions of Cement per ton Unit Electricity consumption of Cement	Cement, Limestone and Plaster

Chemical industry (ISIC 20-21) Energy Intensity CO2 emissions Intensity of Chemical industry	Chemicals

Table 19: *Descriptive Statistics (Italian industrial energy Indicators)*

The table gives a detailed descriptive statistics of the data downloaded from the Odyssee-Mure database.

Indicator Variable in regression models	Odyssee-Mure Indicator Name	Industry	Calculation	Data source	Unit	Period	Data Frequency
$X_{PMEnInt}$	Energy intensity of Primary Metals (at exchange rate)	Primary Metals ISIC 24	Final energy consumption per value added at constant price	Odyssee	koe/EUR2015	2010 – 2020	Annual
$X_{CO2Steel}$	Total CO2 emissions of steel per ton (included electricity)	Steel	CO2 per ton of production	Odyssee	tCO2/t	2010 – 2020	Annual
X_{UConsS}	Unit consumption of crude steel	Steel	Energy consumption per ton of production	Odyssee	toe/t	2010 – 2020	Annual
$X_{NMMEnInt}$	Energy intensity of non-metallic minerals (at exchange rate)	Non metallic Mineral ISIC 23	Final energy consumption per value added at constant price	Odyssee	koe/EUR2015	2010 – 2020	Annual
X_{CO2Cem}	Total CO2 emissions of cement per ton (included electricity)	Cement	CO2 per ton of production	Odyssee	tCO2/t	2010 – 2019	Annual

$X_{UConsELCem}$	Unit consumption of electricity of Cement	Cement	Electricity consumption per production in tons	Odyssee	kWh/t	2010 – 2019	Annual
$X_{ChemEnInt}$	Energy intensity of Chemicals (at exchange rate)	Chemical Industry ISIC 20-21	Final energy consumption per value added at constant price	Odyssee	koe/EUR2015	2010 – 2020	Annual
$X_{CO2Chem}$	Total CO2 intensity of Chemicals (included electricity)	Chemical Industry	CO2 emissions per value added at constant price	Odyssee	kCO2/EUR2015	2010 – 2019	Annual

Since the list of the firms included in each of Terna sectors is not available, approximate tables were produced manually for each year starting from 2010 based on the listed firms belonging to each sector (the data are available on the Borsa Italiana[15] website). Then, the value-weighted sector price-earnings and book-to-market time-series were produced manually based on data contained in Mediobanca annual reports[16]: PE All Metals, BTM All Metals, PE Cement, BTM Cement, PE Chemicals, BTM Chemicals. All the data are at annual level. The period for which price-earnings and book-to-market ratios are available is 2010 – 2018. The price-earnings and book-to-market series were produced manually by means of the following procedure: for each year the list of the companies included in each industrial sector (All Metals, Cement and Chemicals), considering new listings and delistings, was made up on the basis of historical archive data on Borsa Italiana website. Then the market values (Borsa Italiana data referred to the end of June of each year) relative to each year were used to produce the year sum (sector's annual market cap). Next, for each company the market-value coefficients were calculated as the ratio of the company's market cap and the cumulative sector's market cap. After that the companies' price-earnings and book-to-market ratios from Mediobanca annual reports (data relative to the end of December of each year) were multiplicated by the value-coefficients obtained before and the results were summed to get the value-

[15] https://www.borsaitaliana.it/borsa/azioni/all-share/lista.html

[16] http://archiviostoricomediobanca.mbres.it/pubblicazioni/indici_e_dati_relativi_ad_investimenti_in_titoli_quotati.html

weighted sector price-earnings and book-to-market ratios for each year. As soon as the regressions require monthly data and not annual, price-earnings and book-to-market ratios were spread to cover 12 months in each year.

***Table 20**: The list of firms considered for the calculation of sector PE and BTM ratios*

All Metals		Cement		Chemicals	
PE	**BTM**	**PE**	**BTM**	**PE**	**BTM**
DANIELI		BUZZI UNICEM		MONTEFIBRE	
DANIELI &.C RSP		BUZZI UNICEM RSP		MONTEFIBRE RSP	
SOCOTHERM		CALTAGIRONE		ISAGRO	
TENARIS		CEMENTIR HOLDING		ISAGRO SVI PRF	
GRUPPO MINERALI MAFFEI		ITALCEMENTI		SOL	
INTEK GROUP		ITALCEMENTI RSP		SACOM	
INTEK GROUP RNC		RDB		SOCOTHERM	
KME GROUP				BIO ON	
KME GROUP RSP				AQUAFIL	
				ICF GROUP	

Period 2009-2018. Cumulative firm denominations list. PE and BTM ratios subject to the availability of data in Mediobanca reports and to new listings/delistings over the period considered.

The daily data on Italian forward energy prices (relative to MTE market) were downloaded from the official website of the Italian energy market (www.mercatoelettrico.org). The data was then used to calculate the volume-weighted average monthly price series which was then transformed into MoM and YoY series according to the necessity, and, if seasonality was present (MoM series), it was then removed by the Tramo-Seats procedure by means of Demetra+ software.

The monthly data on the Italian inflation index (HICP, Harmonised Index of Consumer Prices[17], not seasonally adjusted, 2015=100), needed for the calculation of the real stock return (RRR = (1 + stock return)/(1 + inflation) -1), were downloaded from the website of the Statistical Data Warehouse of the European Central Bank. Monthly data (levels) for the period Jan 2009 – Mar 2023, and annual change (YoY) for the same period. Then, MoM series were produced manually taking the series of the level data and used in the calculation of the sector real rates of return.

The historical monthly data on the carbon permits' prices were downloaded from www.mercatoelettrico.org website of the Energy Market Manager (GME). Until October 2017 there were four types of Energy Efficiency Certificates (TEE) distinguished on the basis of the kind of energy savings that the firm made:

17 https://sdw.ecb.europa.eu/quickview.do;jsessionid=B1C4EDAD18BE5D8123BAFC8D92B70A33?SERIES_KEY=122.ICP.M.IT.N.000000.4.INX

- type I certificates, issued for primary energy savings due to the reduction of final electricity consumption.
- type II certificates, issued for primary energy savings due to the reduction of natural gas consumption.
- type III certificates, issued for savings of forms of primary energy other than electricity and natural gas achieved in sectors different from the transport sector.
- type IV certificates, issued for savings of forms of primary energy other than electricity and natural gas achieved in the transport sector.

So, only type I certificates were considered in the data series for the present analysis. However, after the 2017 the distinction of three types was substituted by one Unified Type, so, it was impossible to distinguish the certificates relative to the electricity consumption reduction anymore. The obtained final data series is a merge of type I series and the subsequent unified type series. The relative daily data was then volume-weighted and monthly averaged manually. Then, the month-over-month and the year-over-year series were produced and appropriately seasonally adjusted by Demetra+ software if the seasonality was detected.

2.2.2. Methodology

The main reference for the methodology of this research is the first specification of technology in Burnside et al. (1995): the non-substitutability of the energy input by other inputs. This is because a certain amount of electricity is always needed to make the machinery equipment work and it cannot be substituted by any other input for this purpose (Roma and Pirino, 2009). Another peculiar aspect of the energy input is its irreversibility which leads to the difficulty in storage. The entropy is yet another important characteristic which leads to the concept of exergy, the only part of the energy ("useful energy") which fully enters the production process. However, the research which considers the linkage between exergy and stock returns is reserved for future work and will involve a deep study of the physics of energy.

This work studies the linear relationship between individual sectors stock index returns and the explanatory variables listed in equation (50) using the OLS regression. In Burnside et al. (1995) the logarithmic changes are considered. For a relatively restricted dataset (as in this research) a reasonable approximation of the logarithmic transformation and first differentiation is the month-over-month growth rate. Besides it, also the year-over-year growth rate was computed as in Zhi Da et al. (2017).

The electricity consumption variable (EC) was used in the regressions as a lagged variable. Whereas the year-over-year data regressions included the one-month lag of the EC, there were some doubts regarding the EC lag to be chosen for the month-over-month regressions. The reason for that is that the moments when electricity is consumed and the moment when the impact on stock prices becomes visible, may differ significantly. They depend on the average length of the production cycle[18] in each industrial sector and the speed with which the stock market becomes aware of the changes in productivity of this or that industrial sector. The chain of impacts is as follows: Electricity Consumption -> Output (Productivity) -> Market Valuation -> Stock prices -> Stock Returns. The main reference data on industrial production for the stock market is the general Italian Industrial Production Index (IPI), which shows the change in volume of the overall industrial production in Italy with respect to the base year (2010 or, more recently, 2015), and is issued with one and a half months of delay by ISTAT. The electricity consumption of Steel sector is strongly correlated (0,93) with the IPI calculated both with base year 2010 and 2015; the electricity consumption of Cement is also correlated with IPI but the value is different for two versions (for 2010=100 correlation is 0,62, for 2015=100 correlation is 0,81); the electricity consumption of Chemicals has also different correlation with the two versions of IPI (for 2010=100 correlation is 0,46, for 2015=100 correlation is 0,64) (see Appendix A for the relative graphs). So, the time lag between the consumption of energy and the change in stock returns may rightfully be of several months. Judging by the high correlation between IPI and EC, it is probable that the stock market considers the IPI trend coinciding with that of the EC of the Steel sector. Therefore, one can hypothesise that the one-month or the two-months lag of the Steel electricity consumption should be most significant in the regression analysis. For the Cement and the Chemicals sector the answer is less certain and several lags of the electricity consumption variable should be tested. Therefore, an empirical check was due and, thus, the lags from one to six months of the electricity consumption variable for the three energy-intensive Italian industrial sectors were tested to choose the best one to be used in the part of research concerning the month-over-month data.

Also, since electricity consumption series do not entirely reflect the productivity of the firm which depends greatly on the energy efficiency of the equipment, some energy intensity measures (both physical per ton of production and value-added per value in euro of 2015 production) had to enter the OLS regressions as shown in model (40) and later indicated by the simplified model equation (50). In fact, given different efficiencies in the use of energy, the same input will produce a different product output and CO2 emissions. The list of the used energy intensity measures was presented above in the Data section. The justification for their use as linear input variables in the regression is analogous to the justification provided by BER 95 in a specific measure of production intensity called

[18] The length of the production cycle depends on many factors: the type of product which is being produced; whether the plant performs the full production cycle or only a part of it; whether the machinery is up to date from the energy efficiency point of view; the size of a series; the availability of constant supply of raw materials etc.

“line speed” which is a measure of the energy efficiency of the machinery. More details on the matter were presented in Section 2.1.2. The main idea was the existence of a close linkage between the variable electricity consumption and the changes in line speed, the intensity of capital usage, and, therefore, the energy intensity. Having both physical and value-added energy intensities, these variables were tested separately. They could not be used in a regression together because of the multicollinearity issue. The following table shows the high correlation between the energy intensities of the industrial sectors under consideration. These are the correlations between the annual data series of energy intensities. It is clear that the monthly disaggregated time-series are correlated between themselves because they are all correlated to the indicator series of energy price (PUN):

Table 21: *Correlations check between the energy intensities of the energy-intensive industrial sectors.*

Correlations ↓→	*Energy Intensity of* ***Primary Metals*** *(koe/EUR2015)*	*Energy Intensity of* ***Non-Metallic Minerals*** *(koe/EUR2015)*
Energy Intensity of ***Steel*** *(toe/t)*	**0,43**	
Electricity Intensity of ***Cement*** *(kWh/t)*		**0,87**

For the **Steel** sector: correlation between the unit consumption of energy per ton of product of crude steel (toe/t) and the energy intensity of Primary Metals sector (koe/EUR2015). For the **Cement** sector: correlation between the unit consumption of electricity per ton of product (kWh/t) and the energy intensity of Non-Metallic Minerals sector (koe/EUR2015). Sample Period: 2009 – 2020.

The multicollinearity problem also concerns the intensity of CO2 emissions which is also among the energy efficiency measures that are included in the regression equations due to its inverse relationship with the energy efficiency as theoretically explained in the previous section. However, the empirical check is indispensable to confirm that the intensity of CO2 emissions is a proxy for the electricity consumption with reference to the Italian industrial sectors. To give the affirmative answer to this question, there should be high correlation between the sector CO2 emissions intensity and the sector energy intensity. In fact, when similar tests are performed on the Italian energy-intensive industrial sectors, the abovementioned correlations are particularly high:

Table 22: *Correlations check between the energy intensities and CO2 emissions intensity of the energy-intensive industrial sectors.*

Correlations ↓→	*CO2 Intensity of **Steel** (tCO2/t)*	*CO2 Intensity of **Chemicals** (kCO2/EUR2015)*	*CO2 Intensity of **Cement** (tCO2/t)*
*Energy Intensity of **Steel** (toe/t)*	**0,97**		
*Energy Intensity of **Primary Metals** (koe/EUR2015)*	**0,54**		
*Energy Intensity of **Chemicals** (koe/EUR2015)*		**0,75**	
*Electricity Intensity of **Cement** (kWh/t)*			**0,97**
*Energy Intensity of **Non-Metallic Minerals** (koe/EUR2015)*			**0,90**

For the **Steel** sector: correlation between the unit consumption of energy per ton of product of crude steel (toe/t), the energy intensity of Primary Metals sector (koe/EUR2015) and the intensity of CO2 emissions of steel production per ton of product (tCO2/t). For the **Chemical** sector: correlation between the energy intensity per 1€ (base 2015) of production value (koe/EUR2015) and the intensity of CO2 emissions of chemical production per 1€ (base 2015) of production value (kCO2/EUR2015). For the **Cement** sector: correlation between the unit consumption of electricity per ton of product (kWh/t), the energy intensity of Non-Metallic Minerals sector (koe/EUR2015) and the intensity of CO2 emissions of cement production per ton of product (tCO2/t). Sample Period: 2009 – 2020.

Therefore, the intensity of CO2 emissions was rightfully tested on par with energy intensities but not with them in the same regression to prevent the arising of multicollinearity which could bias the results.

Therefore, the equation (50) could not be tested in its full version with all the indicated regressors but only in reduced forms, including one energy efficiency measure at a time.

Besides, also the reduced forms of regressions with only the electricity consumption variable were tested to see the pure impact of the EC on stock returns and then check how the situation changes with the addition of other variables.

The forward energy price variable was added to the regressions following the solution to the maximization and minimisation problems of an energy-intensive firm (a steel company) which was presented in Section 2.1.4. However, the change in forward energy price does not lead to immediate improvements in energy efficiency of the equipment which lead to the increase in the output and the productivity which in turn force a change in the relative stock returns. This delay is very difficult to estimate, and it very much depends on the company's individual decisions in response to the forward energy price change (different elasticities with respect to the energy forward price). Therefore, the time lag was checked empirically by testing the lags of the forward energy price variation from one to six months, and then using the most statistically significant lag in the multiple regression analysis.

The carbon permits' price which was added to the main equation (50) as a control variable even if its use is not justified by the theoretical model. It could work like the forward energy price in boosting the improvement in the energy efficiency of the equipment which then leads to the increase in productivity and a decrease in stock returns (the investors do not ask for higher returns for the risk taken if the company is more productive and, hence, healthier). According to the logics of the speed of adjustment of energy efficiency described in the previous paragraph, the change in carbon permits' price could produce effects with a delay. Therefore, the lags from one to six months were tested and the most significant one was used in the regressions.

So, the analysis starts with the check on the performance of two other popular financial variables in the asset pricing literature: price-earnings ratio (P/E) and book-to-market ratio (B/M) of the industrial sectors under consideration by means of OLS regressions. So, the empirical analysis begins with the regressions of sector book-to-market and price-earnings series against the contemporaneous sector MoM and YoY electricity consumption and the sector energy efficiency measures in order to assess whether the former ratios are related to the growth rate in electricity consumption of the sector corrected for energy efficiency and if so, whether the electricity consumption growth rate may substitute price-earnings and book-to-market ratios in the sector models of prediction of industrial sector stock returns. This analysis is useful to see the channel through which the impact of the electricity consumption on the stock prices occurs (which is the variable, P/E or B/M or none of the two, which reacts to the change in market valuation of the this or that industrial sector due to the change in sector productivity). The regression analysis of this section shows which of the financial ratios (P/E or B/M or none of the two) would be the best to use in the final multiple regression for each industrial sector because their variations are not explained for the most part by the electricity consumption corrected by the energy efficiency measures and, thus, they could add some information to the final predictive model.

The analysis proceeds with the tests on the month-over-month data series (the dependent variable being the MoM growth rate of the industrial sector price index, the independent variables – MoM sector electricity consumption, energy efficiency measures, the MoM growth of the forward energy price and the MoM growth of the carbon permits' price). First, in order to decide which lag of the electricity consumption variable to use, the single-factor regressions were performed. Then, the most statistically significant lag was used in multiple-factor regressions with energy efficiency measures. When the most significant energy efficiency measure was determined, then it was used in yet other regressions with the best lag of the forward energy price change and of the carbon permits' price change.

Then, in addition to the regressions with MoM data, also the regressions with YoY data were performed. Zhi Da et al. used the year-over-year electricity usage growth rate (YoY EC) which above all was useful to remove the seasonality from the series. It is computed as the difference between the energy consumption of the same month of year *t* and of year *t-1*[19]. This procedure is not necessary anymore for the sake of the seasonal adjustment which in this research is computed by the Demetra+ software, however, the regression tests (the OLS procedure, the ordinary least squares) are also carried out on the year-over-year time-series to see whether the results are comparable with those obtained by Zhi Da et al. for the US stock market. The monthly YoY sector price index growth series (the series of returns) acts as the dependent variable in the regression where the independent variables are the monthly YoY sector electricity consumption growth, energy efficiency measures and the forward energy price YoY growth rate.

Finally, the multiple regressions with all the best previously chosen regressors for each of the three energy-intensive Italian industrial sectors (Basic Resources, Construction & Materials and Chemicals) were performed, and the conclusions were drawn.

[19] For instance, the Year-over-year growth of electricity consumption (EC) referred to June 2013 is computed as (EC June 2013 – EC June 2012) / EC June 2012.

2.3. Models with Financial Variables.

In the setting of the model elaborated in this research (equation 39 and equation 41), where the dual output generated only by the energy input impacts the stock returns, it would be highly informative to see whether (and by which channel) the electricity consumption corrected by the energy efficiency measures influences the financial variables (Book-to-Market ratio and Price-Earnings ratio) which are commonly used to predict stock returns. The setting of this study suggests that it occurs through the channel of productivity (output) and sector energy efficiency. The analysis with the inclusion of two most used financial ratios (B/M and P/E) will show if this supposition is correct. Then, if the logics of passing through output and productivity to explain market valuation of the industrial sectors is not entirely plausible for some of the chosen industrial sectors and thus, the percentage of the variation explained by the models with electricity consumption and energy efficiency measures is not high (and the correlation with other regressors is acceptable), it could be useful to add those financial ratios to the selected reduced models for the industrial sectors under consideration to get the augmented models for the optimal explanation of sector stock returns. Because in this case it would mean that B/M and P/E are constructed by considering some other information rather than those referred to production volumes and the greenhouse gasses emitted in the atmosphere, and, hence, they could bring some additional information to the models.

As it was already mentioned before, the electricity consumption alone may increase the output and the productivity of a firm, but it does not say anything about its future perspectives, it does not show if the firm is investing in more efficient productive equipment and, thus, in its own growth. So, the impact on stock returns of an increase in output due to higher electricity consumption may or may not be of the expected sign and magnitude because the market, apart from the volume of production, analyses a series of other data to decide which price the stock should have.

The indicator of future growth of a firm is its B/M ratio (company's book value / the value that the market gives it). If it is high, then the firm is a value-firm whose growth potential is considered low by the market; if it is low, then the market believes that the firm is healthy and has a good growth potential. Considering the data under consideration in this research, the companies that invest in the energy efficiency of their equipment are usually growth firms. Then the energy efficiency measures are the indicator of the firm's virtuous performance and healthy future.

On the other hand, there is the Price-Earnings ratio (company's share market price / book earnings per share) which depends on the firm's earnings, the sales growth, profit margins, the volatility in performance, the debt/equity ratio, the dividend policy, the quality of management, and indicates future earnings growth. When P/E is high, it means that the stock is either overvalued or investors expect high growth rates in the future because the company has invested a lot in its growth. When

P/E is low, the stock is undervalued, and the investors consider it a good buy. Taking the data of this study, all the other determinants of the P/E ratio remaining constant, earnings should depend more on the volume of the output and productivity than on the energy efficiency of the equipment. Then it would be logical to expect high significance of the electricity consumption variable in explaining the variations in the P/E ratio.

Then, in the regressions having the Book-to-market ratio as the dependent variable, the energy efficiency measures are supposed to be significant and to have a positive sign, and in the regressions having the stock returns as the dependent variable, the B/M is supposed to be significant and to have a positive sign as well. Naturally, this does not apply to situations when the energy efficiency of the sector is abnormally high or abnormally low, the results could deviate from what was expected.

Accordingly, in the regressions with the Price-Earnings ratio as the explained variable, the electricity consumption variable (MoM or YoY change) is supposed to be significant and to have a negative sign if it is the main driver of the P/E. In case of the regressions with stock returns the P/E ratio could take different signs based on what the market believes and not only see. Also, the energy efficiency conditions of the industrial sector could be such (e.g. extremely low) that the sign could be reversed.

The market inefficiencies (mispricing of the attributes determining B/M and P/E ratios) could lead to the anomalies in B/M and P/E ratios (e.g. unexpected coefficient signs). Therefore, the regressions are aimed at highlighting the cases when the B/M and the P/E ratios behave according to the expectations, and only in those cases and for those sectors the conclusion is drawn whether they must (or must not) be included in the final sector regression.

Section 2.3.1. regresses the sector book-to-market ratios against the electricity consumption (both month-over-month and year-over-year) alone and in combination with energy efficiency measures. Section 2.3.2 is dedicated to the similar check but this time on the price-earnings ratio.

2.3.1. Electricity Consumption and Book-to-Market

In this section the relationship between the book-to-market ratio (B/M) of each sector index and the variables describing the conditions of production of the industrial sector is investigated. The results of the OLS regression of the B/M on the contemporaneous explanatory variables are presented in what follows for each of the sectors.

2.3.1.1. Month-over-Month data:

The following table serves as the synthetic representation of the OLS regression results of the sector book-to-market ratios against the month-over-month data on electricity consumption and energy efficiency measures for Basic Resources (Metals), Construction & Materials (Cement) and Chemicals sectors.

Table 23: OLS Regressions: Book-to-market ratios of Metals, Cement and Chemicals sectors against MoM electricity consumption of the associated industrial sectors and sector energy efficiency measures.

The regressors and the models tested:

$Y1_t$ is Book-to-market ratio of **Metals** sector at time *t*,
$X_{MoMECS\ t}$ is MoM Seasonally Adjusted Electricity Consumption of Steel sector at time *t*;
$x_{PMEnInt\ t}$ is the Energy intensity of Primary Metals sector (koe/EURO 2015) at time *t*;
$x_{UConsS\ t}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time *t;*
$x_{CO2Steel\ t}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time *t*.

Model 1: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\ t} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\ t} + \beta_2 x_{PMEnInt\ t} + \varepsilon_t$

Model 3: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\ t} + \beta_3 x_{UConsS\ t} + \varepsilon_t$

Model 4: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\ t} + \beta_4 x_{CO2Steel\ t} + \varepsilon_t$

$Y2_t$ is Book-to-Market ratio of **Cement** sector at time *t*,
$x_{MoMECCem\ t}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time t;
$x_{NMMEnInt\ t}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time t;
$x_{UConsC\ t}$ is the Intensity of <u>Electricity</u> Consumption of Cement sector per ton of production (kWh/t) at time t;
$x_{CO2Cem\ t}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time *t*.

Model 5: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\ t} + \varepsilon_t$

Model 6: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\ t} + \beta_2 x_{NMMEnInt\ t} + \varepsilon_t$

Model 7: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\ t} + \beta_3 x_{UConsC\ t} + \varepsilon_t$

Model 8: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\ t} + \beta_4 x_{CO2Cem\ t} + \varepsilon_t$

$Y3_t$ is Book-to-market ratio of **Chemicals** sector at time *t*,
$X_{MoMECChem\ t}$ is MoM Seasonally Adjusted Electricity Consumption of Chemicals sector at time *t*;
$x_{ChemENInt\ t}$ is the Energy intensity of Chemicals sector (koe/EUR2015) at time *t*;
$x_{CO2Chem\ t}$ is the Intensity of CO2 emissions of Chemicals sector (kCO2/EUR2015) at time *t*.

Model 9: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \varepsilon_t$

Model 10: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \beta_2 x_{ChemEnInt\ t} + \varepsilon_t$

Model 11: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \beta_4 x_{CO2Chem\ t} + \varepsilon_t$

	Metals				Cement				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	2.164**	2.120***	1.809**	1.426*	-0.0887	0.0615	-0.0488	0.248	-0.166	0.239	0.0231
	(0.029)	(0.010)	(0.049)	(0.091)	(0.948)	(0.964)	(0.972)	(0.854)	(0.814)	(0.691)	(0.961)
Energy Intensity (value-added)		1.894***				2.768				5.737***	
		(0.000)				(0.115)				(0.000)	
Energy Intensity			5.645***				0.00212				
			(0.000)				(0.745)				
CO2 Intensity				1.817***				6.157**			1.225***
				(0.000)				(0.018)			(0.000)
Constant	0.475***	-0.529***	-0.491**	-0.676***	1.808***	0.691	1.575**	0.515	0.692***	-0.226	-0.256***
	(0.000)	(0.001)	(0.046)	(0.001)	(0.000)	(0.333)	(0.032)	(0.349)	(0.000)	(0.124)	(0.004)
N	107	107	107	107	107	107	107	107	107	107	107
adj. R^2	0.036	0.346	0.170	0.309	-0.009	0.005	-0.018	0.035	-0.009	0.268	0.538
F	4.905	29.04	11.89	24.69	0.00425	1.263	0.0555	2.897	0.0559	20.44	62.71
p	**0.0289****	**9.56e-11*****	**0.0000224*****	**1.68e-09*****	0.948	0.287	0.946	0.0597*	0.814	**3.26e-08*****	**1.36e-18*****
df r	105	104	104	104	105	104	104	104	105	104	104

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the Book-to-Market of Metals sector (the dependent variable in models 1, 2, 3, 4), the book-to-market ratio of the Cement sector (the dependent variable in models 5, 6, 7, 8), the book-to-market ratio of the Chemicals sector (the dependent variable in models 9, 10, 11), the month-over-month change of the electricity consumption of the Steel, Cement and Chemicals sectors (Electricity Consumption) the value-added energy intensity of the Primary Metals, Non-Metal Mineral and Chemicals sectors (Energy Intensity value-added), the physical energy intensity of the Steel sector and the physical electricity intensity of Cement sector (Energy Intensity), the physical CO2 emissions intensity of the Steel sector and the value-added CO2 emissions intensity of Chemicals sector (CO2 Intensity). Sample period: Feb 2010 – Dec 2018.

The table above shows the cumulative regression results which reveal at first glance that the energy efficiency measures all feature the expected (positive) sign meaning that the chain of impacts is consistent with the setting of the elaborated model: energy/CO2 intensities, which are the inverse of the energy efficiency, impact the output and the productivity in the opposite direction; then if the B/M, as well as the stock returns, follow the logics of the elaborated model, they should move in the opposite direction with the energy efficiency (B/M is lower for higher energy efficiency of the firm because the market values highly its growth potential and increases its market value). In fact, the table above shows that this chain of impacts works well. However, the electricity consumption variable, if used alone, is significant only for the Metals sector. The positive sign is consistent with the model setting: the increase in electricity consumption (the decrease in MoM electricity consumption) influences positively the output and the productivity of a firm and then positively stock prices and negatively the B/M and the stock returns. This means that the electricity withdrawals of that sector alone (extremely high amounts with respect to the electricity usage of other industrial sectors), together with energy efficiency measures, can influence the market valuation of the health of the Metals sector. This happens because the production process of this sector is extremely energy-intensive and highly energy efficient, meaning a direct linkage between the quantity of consumed energy and the productivity.

A closer look uncovers that the electricity consumption of the Cement sector, adjusted for energy efficiency, does not explain the variability of the book-to-market ratio of the Cement sector. Only the

CO2 emissions intensity is significant at 5% level but the model which includes it explains only 3,5% of the variability in the sector B/M. As it was shown at the end of Section 2.1. the relative industrial sector is not at all virtuous from the energy efficiency point of view. So, these results are consistent with that information. Therefore, the Book-to-Market ratio of the Cement sector is based on some other information rather than the energy efficiency data.

The other two industrial sectors (Metals and Chemicals) are much more performing in terms of energy efficiency and, in fact, the electricity consumption variable for those sectors corrected by energy efficiency measures (only the energy and CO2 emissions intensities for the Chemicals sector) explains an important part of the variability of the sector book-to-market ratio (up to 35% for the Metals sector and up to 54% for the Chemicals sector). However, if the energy efficiency measures are not used in the model, the B/M of these sectors is explained very little (Metals 3,6%) or not at all (Chemicals). Therefore, the B/M ratios of these two sectors are determined by information on sector energy efficiency which is generally the main indicator of future productivity growth.

2.3.1.2. Year-over-Year data:

Table 24: OLS Regressions: Book-to-market ratios of All-Metals, Cement and Chemicals sectors against YoY electricity consumption of the associated industrial sectors and sector energy efficiency measures.

The regressors and the models tested:

$Y1_t$ is Book-to-market ratio of **Metals** sector at time *t*,
$x_{YoYECS\,t}$ is YoY Electricity Consumption of Steel sector at time *t*;
$x_{PMEnInt\,t}$ is the Energy intensity of Primary Metals sector (koe/EURO 2015) at time *t*;
$x_{UConsS\,t}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time *t;*
$x_{CO2Steel\,t}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time *t*.

Model 1: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\,t} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\,t} + \beta_2 x_{PMEnInt\,t} + \varepsilon_t$

Model 3: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\,t} + \beta_3 x_{UConsS\,t} + \varepsilon_t$

Model 4: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\,t} + \beta_4 x_{CO2Steel\,t} + \varepsilon_t$

$Y2_t$ is Book-to-market ratio of **Cement** sector at time *t*,
$x_{YoYECCem\,t}$ is YoY Electricity Consumption of Cement sector at time *t*;
$x_{NMMEnInt\,t}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time *t*;
$x_{UConsCem\,t}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time *t;*
$x_{CO2Cem\,t}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time *t*.

Model 5: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem\,t} + \varepsilon_t$

Model 6: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem\,t} + \beta_2 x_{NMMEnInt\,t} + \varepsilon_t$

Model 7: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem\,t} + \beta_3 x_{UConsCem\,t} + \varepsilon_t$

Model 8: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem\,t} + \beta_4 x_{CO2Cem\,t} + \varepsilon_t$

$Y3_t$ is Book-to-market ratio of **Chemicals** sector at time *t*,
$x_{YoYECChem\,t}$ is YoY Electricity Consumption of Chemicals sector at time *t*;
$x_{ChemEnInt\,t}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time *t*;

$x_{CO2Chem\,t}$ the Intensity of CO2 emissions of Chemicals sector (kCO2/EUR2015) at time *t*.

Model 9: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \varepsilon_t$

Model 10: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \beta_2\, x_{ChemEnInt\,t} + \varepsilon_t$

Model 11: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \beta_4\, x_{CO2Chem\,t} + \varepsilon_t$

	Metals				Cement				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	-0.638	-0.909	-0.536	-0.497	-0.807	-0.508	-0.785	-0.114	-0.0570	-0.389	-0.724***
	(0.353)	(0.109)	(0.402)	(0.388)	(0.476)	(0.658)	(0.503)	(0.922)	(0.887)	(0.270)	(0.009)
Energy Intensity (value-added)		2.113***				2.463				5.532***	
		(0.000)				(0.193)				(0.000)	
Energy Intensity			5.952***				0.000541				
			(0.000)				(0.939)				
CO2 Intensity				2.044***				5.560*			1.432***
				(0.000)				(0.058)			(0.000)
Constant	0.658***	-0.430**	-0.379	-0.681***	1.712***	0.742	1.654**	0.605	0.663***	-0.218	-0.424***
	(0.000)	(0.010)	(0.155)	(0.002)	(0.000)	(0.326)	(0.033)	(0.309)	(0.000)	(0.175)	(0.000)
N	96	96	96	96	96	96	96	96	96	96	96
adj. R^2	-0.001	0.325	0.135	0.299	-0.005	0.002	-0.016	0.023	-0.010	0.237	0.554
F	0.870	23.91	8.386	21.26	0.513	1.117	0.257	2.103	0.0205	15.75	60.01
p	0.353	**4.19e-09*** **	**0.000448*** **	**2.49e-08*** **	0.476	0.332	0.774	0.128	0.887	**0.00000129*** **	**1.83e-17*** **
df r	94	93	93	93	94	93	93	93	94	93	93

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the Book-to-Market of Metals sector (the dependent variable in models 1, 2, 3, 4), the book-to-market ratio of the Cement sector (the dependent variable in models 5, 6, 7, 8), the book-to-market ratio of the Chemicals sector (the dependent variable in models 9, 10, 11), the year-over-year change of the electricity consumption of the Steel, Cement and Chemicals sectors (Electricity Consumption) the value-added energy intensity of the Primary Metals, Non-Metal Mineral and Chemicals sectors (Energy Intensity value-added), the physical energy intensity of the Steel sector and the physical electricity intensity of Cement sector (Energy Intensity), the physical CO2 emissions intensity of the Steel sector and the value-added CO2 emissions intensity of Chemicals sector (CO2 Intensity). Sample period: Jan 2011 – Dec 2018.

As it can be clearly seen from the table above, if we look only at the energy efficiency measures, the tests on the year-over-year data produce almost the same results as those for the month-over-month data. So, the logic of the elaborated model is again preserved. The energy efficiency measures are still quite essential in the explanation of the sector book-to-market ratios. For the Cement sector, which is not highly energy efficient, only one intensity is statistically significant. Neither model nor variable is statistically significant for this sector (except for the weak significance of the CO2 emissions intensity). The electricity consumption variable of the Metals sector is not significant compared to the month-over-month single-factor tests. However, if the year-over-year electricity consumption is corrected by the energy efficiency measures, the models become immediately highly significant. This result could be due to the fact that energy efficiency measures which are originally presented at annual level gain more weight in the year-over-year tests. Then the B/M, being an annual dummy, relies more on the information that the energy efficiency measures convey. The electricity consumption variable becomes insignificant.

For the Chemicals sector the electricity consumption variable becomes highly significant in explaining the sector B/M ratio when combined with the value-added CO2 intensity. As far as the final model of this sector will include both variables, the B/M ratio will be useless and will only bias the final inference results if added. It is already sufficiently explained (55,4%) by the EC and the CO2 intensity of the Chemicals sector.

As for the Basic Resources sector, as soon as the final YoY model will include not only the YoY electricity consumption but also the physical energy intensity, the share of the explained variability of the B/M ratio will be only 13,5%, hence, it could be reasonable to add it to the final sector model.

For the Construction & Materials sector the final YoY model will include the electricity consumption and the value-added energy intensity of the Cement sector meaning that the sector B/M ratio should also be added to this model given that the former variables do not explain any of its variation.

2.3.2. Electricity Consumption and Price-Earnings.

Now the same check to decide whether this financial variable is necessary in the predictor model of Italian sector stock returns will be performed on the sector price-earnings ratios.

2.3.2.1. Month-over-month data:

Table 25: Regression of Price-earnings ratios of All-Metals, Cement and Chemicals sectors against MoM electricity consumption of the associated industrial sectors and sector energy efficiency measures.

The regressors and the models tested:

$Y1_t$ is Price-Earnings ratio of **Metals** sector at time *t*,
$x_{MoMECS\,t}$ is MoM Seasonally Adjusted Electricity Consumption of Steel sector at time *t*;
$x_{PMEnInt\,t}$ is the Energy intensity of Primary Metals sector (koe/EURO 2015) at time *t*;
$x_{UConsS\,t}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time *t;*
$x_{CO2Steel\,t}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time *t*.

Model 1: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\,t} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\,t} + \beta_2 x_{PMEnInt\,t} + \varepsilon_t$

Model 3: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\,t} + \beta_3 x_{UConsS\,t} + \varepsilon_t$

Model 4: $Y1_t = \beta_0 + \beta_1 x_{MoMECS\,t} + \beta_4 x_{CO2Steel\,t} + \varepsilon_t$

$Y2_t$ is Price-Earnings ratio of **Cement** sector at time *t*,
$x_{MoMECCem\,t}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time *t*;
$x_{NMMEnInt\,t}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time *t*;
$x_{UConsC\,t}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time *t.*
$x_{CO2Cem\,t}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time *t*.

Model 5: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\,t} + \varepsilon_t$

Model 6: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\,t} + \beta_2 x_{NMMEnInt\,t} + \varepsilon_t$

Model 7: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\,t} + \beta_3 x_{UConsC\,t} + \varepsilon_t$

Model 8: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem\,t} + \beta_4 x_{CO2Cem\,t} + \varepsilon_t$

$Y3_t$ is Price-Earnings ratio of **Chemicals** sector at time *t*,
$X_{MoMECChem\,t}$ is MoM Seasonally Adjusted Electricity Consumption of Chemicals sector at time *t*;
$x_{ChemEnInt\,t}$ is the Energy intensity of Chemicals sector (koe/EUR2015) at time *t*;

$x_{CO2Chem\ t}$ is the Intensity of CO2 emissions of Chemicals sector (kCO2/EUR2015) at time *t*.

Model 9: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \varepsilon_t$

Model 10: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \beta_2 x_{ChemEnInt\ t} + \varepsilon_t$

Model 11: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ t} + \beta_4 x_{CO2Chem\ t} + \varepsilon_t$

	Metals				Cement				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	17.30**	17.13**	15.63**	14.25**	0.850	0.967	0.623	1.728	-3.730	-5.856	-4.569
	(0.015)	(0.012)	(0.024)	(0.037)	(0.938)	(0.930)	(0.955)	(0.875)	(0.571)	(0.357)	(0.461)
Energy Intensity (value-added)		7.097***				2.160				-30.07***	
		(0.002)				(0.878)				(0.002)	
Energy Intensity			26.42***				-0.0120				
			(0.009)				(0.817)				
CO2 Intensity				7.488***				16.07			-5.428***
				(0.001)				(0.444)			(0.000)
Constant	3.208***	-0.557	-1.314	-1.538	11.21***	10.34*	12.53**	7.834*	14.65***	19.46***	18.85***
	(0.000)	(0.678)	(0.473)	(0.327)	(0.000)	(0.074)	(0.032)	(0.082)	(0.000)	(0.000)	(0.000)
N	107	107	107	107	107	107	107	107	107	107	107
adj. R^2	0.046	0.124	0.098	0.130	-0.009	-0.019	-0.019	-0.013	-0.006	0.074	0.109
F	6.123	8.479	6.758	8.901	0.00613	0.0148	0.0300	0.299	0.323	5.243	7.480
p	**0.0149****	**0.000388*****	**0.00174*****	**0.00027*****	0.938	0.985	0.970	0.742	0.571	**0.00677*****	**0.000922*****
df r	105	104	104	104	105	104	104	104	105	104	104

p-values in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the Price-Earnings ratio of Metals sector (the dependent variable in models 1, 2, 3, 4), the price-earnings ratio of the Cement sector (the dependent variable in models 5, 6, 7, 8), the price-earnings ratio of the Chemicals sector (the dependent variable in models 9, 10, 11), the month-over-month change of the electricity consumption of the Steel, Cement and Chemicals sectors (Electricity Consumption) the value-added energy intensity of the Primary Metals, Non-Metal Mineral and Chemicals sectors (Energy Intensity value-added), the physical energy intensity of the Steel sector and the physical electricity intensity of Cement sector (Energy Intensity), the physical CO2 emissions intensity of the Steel sector and the value-added CO2 emissions intensity of Chemicals sector (CO2 Intensity). Sample period: Feb 2010 – Dec 2018.

The table above shows that the electricity consumption and the energy efficiency measures of the Metals sector are again highly significant in explaining the tested financial ratio because of the outstandingly energy-intensive production process. However, the percentage of the explained variation of the P/E is not high (max 13%). It is the lowest (4,6%) when the electricity consumption variable is used alone, and this is exactly the way the final MoM model will look like. The electricity consumption variable and the energy efficiency measures relative to the Metals sector feature a positive sign (the opposite of what is usually expected if the P/E is the dependent variable). The correlation matrix in Appendix B shows that B/M and P/E for this sector are highly positively correlated (0,74) which may be due to the exploitation of the scale of production and, hence, the abnormal growth in earnings which surpasses the increase in market value of the sector. Then, the impact of the EC and the energy efficiency measures on the P/E is reversed. Considering the acceptable correlation between the P/E and the MoM electricity consumption, it would be prudent to include the P/E in the final regression for the explanation of the Basic Resources stock returns. However, given the correlation between B/M and P/E of this sector, they should be used in the sector regressions one at a time.

The cumulative regression results table above shows that the MoM electricity consumption of the Cement sector, corrected (or not) by the energy efficiency measures, does not explain the sector price-earnings ratio. None of the sector energy efficiency measures is significant at any acceptable level. As it was said before, this could be because of the low energy efficiency of this industrial sector and because the market could be guided by other information rather than the electricity consumption when it values the health of the industrial sector. Then, the energy and CO2 emissions intensities convey little information to the market about the real productivity of this sector. The inclusion of the sector P/E ratio in the final model explaining the Construction & Materials stock return could improve the regression results.

Similar situation to that of the Metals sector is observed for the Chemicals sector. Again, the models including electricity consumption variable adjusted for energy efficiency are highly significant in explaining the sector P/E ratio meaning that the market values correctly the productive reality and potential of this industrial sector. Still the percentage of P/E variation explained by the models is not high (min 0% with only EC and max 10,9% with CO2 intensity). Besides, considering that the final MoM model for this sector will not include any of the listed energy efficiency measures, also for the Chemicals sector the P/E ratio would be included in the final MoM regression explaining the stock returns of the Chemicals sector.

2.3.2.2. Year-over-year data:

Table 26: Regression of Price-earnings ratios of All-Metals, Cement and Chemicals sectors against YoY electricity consumption of the associated industrial sectors and sector energy efficiency measures.

The regressors and the models tested:

$Y1_t$ is Price-Earnings ratio of All-Metals sector at time *t*,
$X_{YoYECS\ t}$ is YoY Electricity Consumption of Steel sector at time *t*;
$x_{PMEnInt\ t}$ is the Energy intensity of Primary Metals sector (koe/EURO 2015) at time *t*;
$x_{UConsS\ t}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time *t;*
$x_{CO2Steel\ t}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time *t*.

Model 1: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\ t} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\ t} + \beta_2 x_{PMEnInt\ t} + \varepsilon_t$

Model 3: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\ t} + \beta_3 x_{UConsS\ t} + \varepsilon_t$

Model 4: $Y1_t = \beta_0 + \beta_1 x_{YoYECS\ t} + \beta_4 x_{CO2Steel\ t} + \varepsilon_t$

$Y2_t$ is Price-Earnings ratio of Cement sector at time *t*,
$x_{YoYEC\ t}$ is YoY Electricity Consumption of Cement sector at time *t*;
$x_{NMMEnInt\ t}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time *t*;
$x_{UConsCem\ t}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time *t;*
$x_{CO2Cem\ t}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time *t*.

Model 5: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem\ t} + \varepsilon_t$

Model 6: $Y2_t = \beta_0 + \beta_1\, x_{YoYECCem\,t} + \beta_2\, x_{NMMEnInt\,t} + \varepsilon_t$

Model 7: $Y2_t = \beta_0 + \beta_1\, x_{YoYECCem\,t} + \beta_3\, x_{UConsCem\,t} + \varepsilon_t$

Model 8: $Y2_t = \beta_0 + \beta_1\, x_{YoYECCem\,t} + \beta_4\, x_{CO2Cem\,t} + \varepsilon_t$

$Y3_t$ is Price-Earnings ratio of Chemicals sector at time *t*,
$x_{YoYEC\,t}$ is YoY Electricity Consumption of Chemicals sector at time *t*;
$x_{ChemEnInt\,t}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time *t*;
$x_{CO2Chem\,t}$ is the Intensity of CO2 emissions of Chemicals sector (kCO2/EUR2015) at time *t*.

Model 9: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \varepsilon_t$

Model 10: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \beta_2\, x_{ChemEnInt\,t} + \varepsilon_t$

Model 11: $Y3_t = \beta_0 + \beta_1\, x_{YoYECChem\,t} + \beta_4\, x_{CO2Chem\,t} + \varepsilon_t$

	Metals				Cement				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	-13.99***	-14.91***	-13.56***	-13.47***	34.61***	35.96***	35.98***	38.99***	-18.15***	-17.43***	-17.47***
	(0.004)	(0.001)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Energy Intensity (value-added)		7.166***				11.12				-12.12	
		(0.005)				(0.413)				(0.168)	
Energy Intensity			24.63**				0.0336				
			(0.025)				(0.505)				
CO2 Intensity				7.510***				35.15*			-1.479
				(0.003)				(0.095)			(0.333)
Constant	4.770***	1.082	0.478	-0.151	12.52***	8.135	8.910	5.518	14.37***	16.30***	15.49***
	(0.000)	(0.413)	(0.803)	(0.928)	(0.000)	(0.136)	(0.107)	(0.197)	(0.000)	(0.000)	(0.000)
N	96	96	96	96	96	96	96	96	96	96	96
adj. R^2	0.077	0.143	0.116	0.149	0.155	0.152	0.150	0.171	0.263	0.270	0.262
F	8.907	8.930	7.247	9.339	18.42	9.518	9.382	10.81	34.88	18.58	17.90
p	**0.00362*** **	**0.000283*** **	**0.00119*** **	**0.000201*** **	**0.0000429*** **	**0.000173*** **	**0.000194*** **	**0.0000599*** **	**5.56e-08*** **	**0.000000163*** **	**0.000000265*** **
df_r	94	93	93	93	94	93	93	93	94	93	93

p-values in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the Price-Earnings ratio of Metals sector (the dependent variable in models 1, 2, 3, 4), the price-earnings ratio of the Cement sector (the dependent variable in models 5, 6, 7, 8), the price-earnings ratio of the Chemicals sector (the dependent variable in models 9, 10, 11), the year-over-year change of the electricity consumption of the Steel, Cement and Chemicals sectors (Electricity Consumption) the value-added energy intensity of the Primary Metals, Non-Metal Mineral and Chemicals sectors (Energy Intensity value-added), the physical energy intensity of the Steel sector and the physical electricity intensity of Cement sector (Energy Intensity), the physical CO2 emissions intensity of the Steel sector and the value-added CO2 emissions intensity of Chemicals sector (CO2 Intensity). Sample period: Jan 2011 – Dec 2018.

The table above shows an opposite situation with respect to the same tests performed on the B/M ratio. Here all the YoY electricity consumption variables are highly significant in explaining the variation in sector P/E ratios. Here the market correctly relates the growth in earnings in Metals and Chemicals sectors to their market valuation (the negative sign is consistent with the logic of the model setting). The Cement sector presents once again an anomaly which can be explained by the high growth in earnings of the sector due to the year-over-year change in electricity consumption and slow market adjustment to this news. So, here a market mispricing takes place.

The energy efficiency measures are highly significant only for the Metals sector (the CO2 emissions intensity is weakly significant in the regression for the Cement sector). Their signs of the coefficients are again positive, confirming the presence of an anomaly. Probably, the sign is due to a very high growth in earnings which is, however, linked more to the growth in energy efficiency and not in production volumes. For the Cement sector the increase in electricity consumption, and the consequent increase in the intensity of CO2 emissions, brought to higher volumes of production which influenced a high growth in earnings which resulted higher than the market adjustment of the stock price. Therefore, the relative coefficients resulted positive which is not consistent with the model setting. The general lack of significance of the energy efficiency measures is compensated by the high significance of the electricity consumption which incorporates all the information at the basis of the construction of P/E ratios.

It is possible to observe from the regression results that the YoY electricity consumption of the Metals sector corrected by the physical energy intensity explains 11,6% of the variability of the P/E of the Metals sector; the YoY electricity consumption of the Cement sector corrected by the sector value-added energy intensity explains 15,2% of the variability of the sector P/E; the YoY electricity consumption of the Chemicals sector alone explains 26,3% of the changes in sector P/E.

Then, giving the limited explanatory power over the P/E, correlations permitting, it would be reasonable to include the sector P/E ratio in the final YoY regressions of Basic Resources and Construction & Materials sectors. It will not be used in the final regression of the Chemicals sector because the P/E is highly correlated with the electricity consumption variable of this sector.

2.4. Regressions

What follows is the regression analysis performed on the electricity consumption, energy efficiency measures, the forward energy price change, the carbon price change, and financial ratios (book-to-market, B/M, and price-earnings, P/E), the dependent variable being the month-over-month or the year-over-year change in industrial sector stock returns corrected for inflation.

The energy efficiency measures are expected to add statistical significance to the regressions quite unevenly across the industrial sectors. The reasons for this intuition are multiple (Lapillonne, 2016): and are not captured by the simplified fixed coefficient model for return developed in Section 2:the energy consumption of some firms could depend more on the fact that some large equipment does not work at full capacity and, therefore, is used less efficiently, or that a part of energy consumption is linked to non-technical changes (the decision to shift the production to other items which require less/more energy consumption during the production process; or a massive closure of obsolete and less efficient production facilities). Both these issues are not accommodated in a Leontief technology.

It is also expected that if the energy-based model correctly represents results, the financial ratios would lose their predictive power over the stock returns when the electricity consumption and energy efficiency variables are included in the analysis. This could happen if the theoretical setting of this research is true to life and the electricity consumption passes through the productivity in its influence on stock returns. And as soon as the financial ratios are based on the market valuation of the firm's performance, it is plausible that the market builds its opinion on the expectation of future productivity of the firm. So, the channel of productivity works for both the electricity consumption and the financial ratios, but the former variable enters the chain before, on the business level.

The following tests will show if these intuitions are correct.

2.4.1. Month-over-month data

The financial operators, like portfolio managers and investors, are interested in predicting the immediate stock price changes (stock returns). The most informative are the price variations relative to the previous month which reflect the changes in firm's productivity due to the alteration of the quantity of productive inputs and firm's productive decisions. That is why the tests with the month-over-month data are due.

The analysis is divided in three steps: first, the single-factor models with the lags of the electricity consumption variable are regressed to choose the best performing lag to be used in further analysis. Then the reduced versions of the regressions are performed (only with energy efficiency measures) to choose one energy efficiency measure, if any, to be used in further tests. The measures are highly correlated between themselves, so the contemporaneous use of all three of them in a regression would give rise to the multicollinearity issue. Then, after having chosen the energy efficiency measure to be used (or having decided not to use any of them), the forward energy price change variable and the carbon permits' price change variable are added to the regressions.

Since the production cycle length differs between the industrial sectors and the business cycle data on Italian industrial sectors is issued with a few months of delay, for each of the energy-intensive industrial sectors (Basic Resources, Construction & Materials, Chemicals) 6 models with the sector electricity consumption lagged variable (lags going from 1 to 6 months) are regressed with the OLS procedure. In this manner the first statistically significant lag is identified. The chosen lag is used as a reference time point for the calculation of the lags of other regressors (energy efficiency measures etc.) that will adjust the impact of the electricity consumption variable in final regressions.

For the Basic Resources sector the chosen lag of the electricity consumption variable is the six-months lag (Table 33 in Appendix C), for the Construction & Materials sector – the three-months lag (Table 35 in Appendix C), for the Chemicals sector – the one-month lag (Table 36 in Appendix C).

The month-over-month change in the electricity consumption of Nonferrous Metals sector, which was also provided by Terna, is not at all statistically significant in explaining the variation of the MoM Basic Resources price index (see Table 34 in Appendix C) and worsens the performance of the EC Steel lags. So, the electric energy consumption of NF Metals sector was dropped from the further analysis.

Then the lagged electricity consumption variables are used in multiple regressions with energy efficiency measures lagged by the same number of months as the relative sector electricity consumption.

As it can be seen from the correlation matrices in Appendix B, the sector energy efficiency measures are always highly correlated between themselves, so it is reasonable to use only one (energy or CO2) intensity at a time in the regressions.

Table 37: OLS Regressions: MoM Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the MoM Electricity of Steel, Cement and Chemicals sectors and energy efficiency measures.

$Y1_t$ is MoM Basic Resources Stock Return at time t,

$x_{MoMECS(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of Steel sector at time (*t-6)*;

$x_{PMEnInt(t-6)}$ is the Energy intensity of Basic Metals sector (koe/EURO 2015) at time (*t-6)*;
$x_{UConsS(t-6)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-6)*;
$x_{CO2Steel(t-6)}$ is the Intensity of CO2 emissions of Steel sector (tCO_2/t) at time (*t-6*).

Model 1: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \varepsilon_t$

Model 2: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_2 x_{PMEnInt(t-6)} + \varepsilon_t$

Model 3: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_3 x_{UConsS(t-6)} + \varepsilon_t$

Model 4: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_4 x_{CO2Steel(t-6)} + \varepsilon_t$

$Y2_t$ is MoM Construction & Materials Stock Return at time t,
$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time (*t-3)*;
$x_{NMNEnInt(t-3)}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time (*t-3)*;
$x_{UConsC(t-3)}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time (*t-3)*;
$x_{CO2Cement(t-3)}$ is the Intensity of CO2 emissions of Cement sector (tCO_2/t) at time (*t-3*).

Firstly, the regressions with energy efficiency measures are performed.

Model 5: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \varepsilon_t$

Model 6: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{NMMEnInt(t-3)} + \varepsilon_t$

Model 7: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_3 x_{UConsC(t-3)} + \varepsilon_t$

Model 8 : $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_4 x_{CO2Cement(t-3)} + \varepsilon_t$

$Y3_t$ is MoM Chemicals Stock Return at time *t*,
$x_{MoMECChem(t-1)}$ is MoM Seasonally Adjusted Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{ChemEnInt(t-1)}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time (*t-1)*;
$x_{CO2Chem(t-1)}$ is the Intensity of CO2 emissions of Chemicals sector (kCO_2/EURO 2015) at time (*t-1)*.

Model 9: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-1)} + \varepsilon_t$

Model 10: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-1)} + \beta_2 x_{ChemEnInt(t-1)} + \varepsilon_t$

Model 11: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-1)} + \beta_4 x_{CO2Chem(t-1)} + \varepsilon_t$

	Basic Resources				Construction & Materials				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	0.560***	0.555***	0.556***	0.562***	0.0449*	0.0501**	0.305***	0.307***	-0.382**	-0.381**	-0.353*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.065)	(0.044)	(0.001)	(0.001)	(0.048)	(0.050)	(0.082)
Energy Intensity value added		-0.0628				0.124				0.0262	
		(0.397)				(0.268)				(0.921)	
Energy Intensity			-0.412				0.000687*				
			(0.169)				(0.075)				
CO2 Intensity				-0.0652				0.257*			0.00417
				(0.323)				(0.093)			(0.923)
Constant	-0.0513***	-0.0178	0.0202	-0.00937	0.00362	-0.0455	-0.0767*	-0.0548*	0.00195	-0.00213	-0.000836
	(0.000)	(0.670)	(0.706)	(0.833)	(0.593)	(0.310)	(0.069)	(0.084)	(0.794)	(0.960)	(0.980)
N	124	124	124	124	124	124	119	119	124	124	119
adj. R^2	0.137	0.135	0.143	0.137	0.020	0.022	0.090	0.088	0.024	0.016	0.009
F	20.47	10.57	11.27	10.73	3.465	2.356	6.849	6.660	3.989	1.983	1.548
p	**0.0000141 *****	**0.0000585 *****	**0.0000324 *****	**0.0000514 *****	0.0651*	0.0992*	**0.00154*****	**0.00183*****	**0.048****	0.142	0.217
df_r	122	121	121	121	122	121	116	116	122	121	116

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month Basic Resources stock return corrected for inflation, the month-over-month Construction & Materials stock return corrected for inflation, the month-over-month Chemicals stock return corrected for inflation; the month-over-month electricity consumption of Steel sector lagged by six months, the month-over-month electricity consumption of Cement sector lagged by three months, the month-over-month electricity consumption of Chemicals sector lagged by one month, and the energy efficiency measures (the value-added energy intensity of Primary Metals sector lagged by six months, the physical energy intensity of Steel sector lagged by six months, the physical CO2 emissions intensity of Steel sector lagged by six months, the value-added energy intensity of Non-metal Minerals sector lagged by three months, the physical electricity intensity of Cement sector lagged by three months, the physical CO2 emissions intensity of Cement sector lagged by three months, the value-added energy intensity of Chemicals sector lagged by one month, the value-added CO2 emissions intensity of Chemicals sector lagged by one month. Sample period: Feb 2010 – Dec 2019.

The table above, first, confirms the base of the theoretic model elaborated in this research and, hence, shows the predictor power of the industrial electricity consumption over the industrial sector stock returns (by impacting the productivity). The sector month-over-month electricity consumption variable, appropriately lagged, is always statistically significant if used alone (models 1, 5, 9). The sign (positive) of the coefficient of the EC variable for Basic Resources and Construction & Materials sectors is consistent with the model setting while the sign (negative) of the EC Chemicals is not. The Chemicals sector is the most performing from the point of view of energy efficiency (see Figure 7). Besides, it is the second sector in Italy for the consumption of electric energy and the most sensitive sector to the price of electricity because it is largely exposed to the international competition. This means that the sector transforms quickly in response to the changes in energy price. These changes may be structural (internal articulation of production process, changes in line of production) or from the point of view of energy intensity[20]. Therefore, the negative sign of the regression coefficient means that the speed of improvement of the Chemicals' energy efficiency is so fast that it reverses the sign of the impact of the electricity consumption on productivity (so even if the electricity consumption is reduced, the productivity remains at the same level or may even increase a little). On the other hand, the negative sign could mean a fast structural transformation of the production line in response to some external shocks.

The tested theoretical model also adds the presence of the incentives for the firms to further increase their energetic efficiency because it will help them to increase productivity. Then the energy efficiency measures enter the explanation.

Neither efficiency measure is statistically significant at any acceptable level in the regressions from (2) to (4) for the Basic Resources sector. The Steel sector being highly energy efficient and being the top consumer of electric energy in Italy, its electricity consumption variable already incorporates all the information useful for the prediction of the relative stock returns. The correcting function of the energy efficiency measures is needless here. Therefore, neither energy efficiency measure could be considered for further analysis of this sector.

The Construction & Materials sector is not at all energy efficient (see Figure 7), then, the energy

[20] http://federchimica.it/dati-e-analisi/conoscere-l'industria-chimica

efficiency measures should exercise their correcting impact on the sector electricity consumption. In fact, the physical energy intensity and the CO2 emissions intensity are both significant with positive coefficients (confirming the correcting effect according to the model setting). The physical energy intensity performs slightly better; hence, it will be used in further analysis of this industrial sector.

The same situation as for the Basic Resources sector, is observed for the Chemicals sector: the energy efficiency measures are not statistically significant in the regressions because the electricity consumption already includes all the information useful for the prediction of the sector stock returns.

However, the performance of the energy efficiency measures in the month-over-month regressions should be considered permitting a certain degree of bias because the monthly series of the intensities were artificially generated out of annual data. It is also no wonder to find the significance of these energy efficiency measures at the monthly level rather low if not completely absent. Following this logic, the year-over-year tests should produce more prominent inference results. The next subsection will prove or reject this hypothesis.

But before moving to the tests on year-over-year, the second step of the analysis of the month-over-month data is due. It consists in integrating the regression analysis with the forward electricity price change and the carbon permits' price change. The lags of those variables are chosen in such a way as to produce the best inference results (see Tables 38, 39, 40, 41, 42 and 43 in Appendix C). Then, the multiple-factor regressions are run.

Table 44: OLS Regressions: MoM Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the MoM Electricity of Steel, Cement and Chemicals sectors, energy efficiency measures, forward energy price change and carbon permits' price change.

$Y1_t$ is MoM Basic Resources Stock Return at time *t*,
$x_{MoMECS(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of Steel sector at time (*t-6)*;
$x_{MoMEP(t-5)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-5);*
$x_{MoMPCO2(t-3)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-3).*

Model 12: $Y1_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_4 x_{MoMEP(t-5)} + \beta_6 x_{MoMPCO2(t-3)} + \varepsilon_t$

$Y2_t$ is MoM Construction & Materials Stock Return at time *t*,
$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time (*t-3)*;
$x_{UConsC(t-3)}$ is the Intensity of <u>Electricity</u> Consumption of Cement sector per ton of production (kWh/t) at time (*t-3);*
$x_{MoMEP(t-4)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-4);*
$x_{MoMPCO2(t-1)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-1).*

Model 13: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{UConsC(t-3)} + \beta_3 x_{MoMEP(t-4)} + \beta_5 x_{MoMPCO2(t-1)} + \varepsilon_t$

$Y3_t$ is MoM Chemicals Stock Return at time *t*,
$x_{MoMECChem\,(t-1)}$ is MoM Seasonally Adjusted Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{MoMEP(t-5)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-5);*
$x_{MoMPCO2(t-3)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-3).*

Model 14: $Y3_t = \beta_0 + \beta_1 X_{MoMECChem\,(t-1)} + \beta_4 X_{MoMEP(t-5)} + \beta_6 X_{MoMPCO2(t-3)} + \varepsilon_t$

	(12) Basic Resources	(13) Construction & Materials	(14) Chemicals
Electricity Consumption	0.561***	0.320***	-0.360*
	(0.000)	(0.001)	(0.062)
Electricity Intensity		0.00074*	
		(0.055)	
Fwd Energy Price	-0.123	-0.162*	-0.203*
	(0.323)	(0.089)	(0.058)
CO2 Price	0.0854	0.0742	0.169**
	(0.297)	(0.228)	(0.016)
Constant	-0.0526***	-0.0829**	-0.00102
	(0.000)	(0.047)	(0.890)
N	124	119	122
adj. R^2	0.138	0.111	0.085
F	7.560	4.670	4.727
p	**0.000113*** **	**0.00158*** **	**0.00376*** **
df r	120	114	118

p-values in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month stock return of the Basic Resources sector corrected for inflation, : the month-over-month stock return of the Construction & Materials sector corrected for inflation, the month-over-month stock return of the Chemicals sector corrected for inflation, the month-over-month change of the electricity consumption of the Steel sector lagged by six months, the month-over-month change of the electricity consumption of the Cement sector lagged by three months, the month-over-month change of the electricity consumption of the Chemicals sector lagged by one month, , the physical electricity intensity of the Cement sector lagged by three months, the month-over-month forward energy price change lagged by five months, the month-over-month forward energy price change lagged by four months, the month-over-month carbon permits' price change lagged by three months, , the month-over-month carbon permits' price change lagged by one month . The Sample period: Feb 2010 – May 2020.

Judging by the results in the table above and in Table 37, the month-over-month change in electricity consumption is confirmed to be an important predictor of industrial sector stock returns.

The EC of the Steel sector explains up to 14% of the variation in stock returns of the Basic Resources sector, and it incorporates all the information on energy efficiency of this sector: neither energy efficiency measure is statistically significant in the regressions. Besides, neither the forward energy price nor the carbon permits' price are statistically significant in this model. The boosters of the improvement of energy efficiency do not work for this sector. This can be explained as follows: this industrial sector is highly energy efficient with extremely energy intensive production with high volumes of output, thus, the increase in scale of production compensates the increase in production costs caused by the increase in forward energy price. The price of carbon permits has no impact meaning that this sector receives enough carbon permits to cover its CO2 emissions.

The EC of the Cement sector explains 11% of the variation in stock returns of the Construction & Materials sector with the assistance of one of the direct energy efficiency measures, namely the electricity intensity (the regression analysis with the CO2 intensity of this sector produces slightly worse results, see Table 45 in Appendix C), and one of the boosters of energy efficiency, the forward energy price change. Their statistical significance in the model is justified by the fact that this industrial sector is not very efficient from the energetic point of view and not big enough to compensate the increase in production costs (the increase in forward energy price) by the increase of the volumes of production. The carbon permits' price change is not significant in the model meaning that this sector receives enough green certificates to cover its CO2 emissions and does not need to buy more of them because they are not sufficient.

Just like for the other two sectors, also the model of the Chemicals sector explains a significant share (up to 9%) of the variation of the relative stock returns. The electricity consumption is statistically significant and presents a negative sign (due to the increasing high energy efficiency of the sector). Both price change variables are statistically significant in the model. In particular, the carbon permits' price change is significant and has a positive coefficient (not consistent with the theory). Differently from the forward energy price, this variable indicates the carbon price not only referred to the future but also referred to the present moment. And as far as the energy efficiency of the Chemicals sector grows at a very high rate, it mitigates the negative impact of the increase of the price of carbon permits (the decrease in the MoM change of carbon prices) on the productivity of the firms. Therefore, the stock price is still high, and the stock return is still low. Hence, the positive regression coefficient is logical to expect. The reduction in the MoM change in forward energy price (negative coefficient for the Chemicals and the Construction & Materials sectors) equal to the increase in the level of the forward energy price, though, boosters the improvement of energy efficiency of the sector because it impacts negatively the productivity, the stock price goes down and the stock returns go up.

In short, it is possible to conclude that that the month-over-month change in electricity consumption corrected, if needed, by energy efficiency measures and accompanied by the variables serving occasionally as boosters of improvement of energy efficiency, explains industrial sectors' stock returns.

2.4.2. Year-over-year data

Following the work by Zhi Da et al. (2017): regressions with year-over-year (YoY) sector price indices as the dependent variables and year-over-year sector electricity consumption as the explanatory variables were performed on three energy-intensive Italian industrial sectors (Basic Resources, Construction & Materials, Chemicals) using the variables justified by the theoretical model of equation (50) elaborated in the previous section. The analysis is divided in two steps: first, the regressions with only energy efficiency measures are tested and one, if any, energy efficiency measure chosen to be used in further tests. Once again, the contemporaneous use of the energy efficiency measures is impossible due to the high correlation between them. After that the forward energy price change variable and the carbon permits' price change variables are added to the regression and the second test is performed.

Basic Resources and Chemicals sectors greatly improved their energy efficiency (see Figure 7) in the recent ten years while their energy consumption did not move significantly (see Figure 16). In turn the Construction & Materials sector ("Non-Metallic Minerals" in the figures) did not show any significant improvements of the energy efficiency while the energy consumption got reduced in a more pronounced manner. Still, the speed of this change is not high enough to see the year-over-year difference lagged only by one month. Several lags were tested (see Table 46 in Appendix C) and the most significant one (a four-months lag) was chosen for further analysis.

Table 47: OLS Regressions: YoY Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the YoY Electricity of Steel, Cement and Chemicals sectors and energy efficiency measures.

$Y1_t$ is YoY Basic Resources Stock Return at time t,
$x_{YoYECS(t-1)}$ is YoY Electricity Consumption of Steel sector at time (*t-1)*;
$x_{PMEnInt(t-1)}$ is the Energy intensity of Basic Metals sector (koe/EURO 2015) at time (*t-1)*;
$x_{UConsS(t-1)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-1)*;
$x_{CO2Steel(t-1)}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time (*t-1)*.

Model 1: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \varepsilon_t$

Model 2: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_2 x_{PMEnInt(t-1)} + \varepsilon_t$

Model 3: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_3 x_{UConsS(t-1)} + \varepsilon_t$

Model 4: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_4 x_{CO2Steel(t-1)} + \varepsilon_t$

$Y2_t$ is YoY Construction & Materials Stock Return at time t,
$x_{YoYECCem(t-4)}$ is YoY Electricity Consumption of Cement sector at time (*t-4)*;
$x_{NMNEnInt(t-4)}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time (*t-4)*;
$x_{UConsC(t-4)}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time (*t-4)*;
$x_{CO2Cement(t-4)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-4)*.

Model 5: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \varepsilon_t$

Model 6: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \beta_2 x_{NMMEnInt(t-4)} + \varepsilon_t$

Model 7: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \beta_3 x_{UConsC(t-4)} + \varepsilon_t$

Model 8 : $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \beta_4 x_{CO2Cement(t-4)} + \varepsilon_t$

$Y3_t$ is YoY Chemicals Stock Return at time *t*,
$x_{YoYECChem(t-1)}$ is YoY Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{ChemEnInt(t-1)}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time (*t-1)*;
$x_{CO2Chem(t-1)}$ is the Intensity of CO2 emissions of Chemicals sector (kCO_2/EURO 2015) at time (*t-1)*.

Model 9: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \varepsilon_t$

Model 10: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_2 x_{ChemEnInt(t-1)} + \varepsilon_t$

Model 11: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_4 x_{CO2Chem(t-1)} + \varepsilon_t$

	Basic Resources				Construction & Materials				Chemicals		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	0.891***	0.871***	0.710***	0.687***	-0.284	-0.305*	-0.399	-0.374	0.291	0.426	0.721**
	(0.000)	(0.000)	(0.003)	(0.004)	(0.123)	(0.093)	(0.115)	(0.147)	(0.347)	(0.158)	(0.013)
Energy Intensity value added		0.0782				0.822**				-2.387***	
		(0.667)				(0.026)				(0.002)	
Energy Intensity			2.186***				0.00212				
			(0.002)				(0.131)				
CO2 Intensity				0.481***				0.884			-0.624***
				(0.003)				(0.125)			(0.000)
Constant	-0.0505**	-0.0905	-0.422***	-0.353***	0.0537**	-0.269*	-0.175	-0.123	0.0103	0.379***	0.487***
	(0.012)	(0.343)	(0.001)	(0.001)	(0.042)	(0.067)	(0.239)	(0.277)	(0.676)	(0.002)	(0.000)
N	113	113	113	113	113	113	108	108	113	113	108
adj. R^2	0.107	0.101	0.174	0.169	0.013	0.047	0.039	0.040	-0.001	0.071	0.179
F	14.46	7.271	12.81	12.37	2.419	3.792	3.197	3.240	0.892	5.310	12.66
p	**0.000234*** **	**0.00108*** **	**0.0000099*** **	**0.000014*** **	0.123	**0.0256** **	**0.0449** **	**0.0431** **	0.347	**0.006*** **	**0.000012*** **
df r	111	110	110	110	111	110	105	105	111	110	105

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year Basic Resources stock return corrected for inflation, the year-over-year Construction & Materials stock return corrected for inflation, the year-over-year Chemicals stock return corrected for inflation; the year-over-year electricity consumption of Steel sector lagged by one month, the year-over-year electricity consumption of Cement sector lagged by four months, the year-over-year electricity consumption of Chemicals sector lagged by one month, and the energy efficiency measures: the value-added energy intensity of Primary Metals sector lagged by one month, the physical energy intensity of Steel sector lagged by one month, the physical CO2 emissions intensity of Steel sector lagged by one month, the value-added energy intensity of Non-metal Minerals sector lagged by four months, the physical electricity intensity of Cement sector lagged by four months, the physical CO2 emissions intensity of Cement sector lagged by four months, the value-added energy intensity of Chemicals sector lagged by one month, the value-added CO2 emissions intensity of Chemicals lagged by one month. Sample period: Feb 2011 – May 2020.

The table above shows a different situation with respect to the same table for the month-over-month data: the electricity consumption variable is not always statistically significant in explaining the industrial sector stock returns. In single-factor regressions it is significant only for the Basic Resources sector which is consistent with the available information: also, the year-over-year growth in electricity consumption is significant for the most energy-intensive industrial sector in Italy. Besides, the energy efficiency measures (which feature positive coefficients consistent with the theory) confirm the impact of the electricity consumption variable on the sector stock returns. If the physical energy intensity is added to the regression, the adjusted coefficient of determination is 17,4% (slightly higher than for the model with the CO2 intensity: 16,9%). Also, this measure was significant at 20% (but with the “wrong” sign) in the month-over-month regression. Therefore, this intensity is kept for further analysis.

The models relative to the Construction & Materials sector present a more realistic situation given that it is almost the least efficient industrial sector in Italy from the energetic point of view (the least being the Machinery sector, see Figure 7): the regression coefficient of the electricity consumption variable is negative meaning that the increase in the electricity usage does not lead to the increase in the output and productivity which remain the same or may even decrease a little. This happens when the firms do not invest in a more efficient equipment which gradually becomes more and more obsolete. This process is not fast, that is why the numbers show its effects only when the year-over-year comparison is done.

The electricity consumption of the Chemicals sector is significant, if combined with one of the energy efficiency measures, and presents the "correct" sign of the coefficient (positive) consistent with the theory. In the test of the month-over-month data the same variable featured a negative sign. This means that the abnormal situation due to very high energy efficiency values of this sector (lower electricity usage to produce the same, or even slightly higher, output) is visible only with high frequency statistics while the year-over-year change shows a more "normal" situation consistent with the theory of this study.

One of the important differences between the year-over-year and the month-over-month data is that while the second type shows the current immediate changes in the statistics, the first type also shows some fluctuations which are more visible in the long run. This concerns, for example, sales and earnings. Then it is not surprising that the value-added energy and CO2 emissions intensities may play a more important role in these tests. For example, the value-added energy intensity of the Cement sector is highly significant and presents the consistent sign (positive), and hence, corrects the impact of the sector electricity consumption change on the Construction & Materials stock returns (the EC variable becomes significant). This could be because firms of the sector rise the price of their products or make structural changes and start producing products for the high value segment. However, the sign of the EC regression coefficient is negative (not consistent). This means that at year-over-year level the overall (low and stagnant) energy efficiency of the Construction & Materials sector is more visible, and higher electricity usage cannot improve the productivity but only makes it remain stable which is valued negatively by the market which reduces the stock price and increases the requested stock return.

Therefore, the value-added energy intensity is used in further tests for the Construction & Materials sector. Besides, both value-added intensities are highly significant for the Chemicals sector but only the CO2 intensity makes the year-over-year electricity consumption of the Chemicals sector significant in explaining the sector stock returns. The regression coefficient of the latter energy efficiency measure is negative which is counterintuitive at first glance with respect to the theoretical setting. However, as it was already mentioned for the month-over-month tests, the Chemicals sector is extraordinarily energy efficient. Therefore, the increase in CO2 emissions (or the energy consumption) per value of production measured in 1 Euro of 2015 cannot impact the energy efficiency in a sufficient way to lead to the reduction of productivity. The energy efficiency grows extremely fasts and brings the productivity to the level expected after the increase in energy input. Thus, the regression coefficient of the value-added CO2 intensity is negative instead of positive.

What follows is the regression analysis of the sector stock returns (Basic Resources, Construction & Materials, Chemicals) vs year-over-year electricity consumption of the Steel, the Cement and the Chemicals sectors with the chosen energy efficiency measures, the forward energy price change and the carbon permits' price change. For the Basic Resources sector only the YoY forward energy price change was used because the YoY carbon price change is highly correlated with the YoY electricity consumption of the Steel sector (see Appendix B for the relative correlation matrices). For the same reason for the Chemicals sector only the YoY carbon price change was used in the regression – the YoY forward energy price is highly corelated with the YoY electricity consumption of the Chemicals sector.

Table 48: OLS Regressions: YoY Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the YoY Electricity of Steel, Cement and Chemicals sectors with chosen energy efficiency measures, YoY forward energy price change, YoY carbon permits' price change.

$Y1_t$ is YoY Basic Resources Stock Return at time *t*,
$x_{YoYECS(t-1)}$ is YoY Electricity Consumption of Steel sector at time (*t-1)*;
$x_{UConsS(t-1)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-1)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at the MTE market at time (*t-1);*

Model 12: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_3 x_{UConsS(t-1)} + \beta_5 x_{YoYEP(t-1)} + \varepsilon_t$

$Y2_t$ is YoY Construction & Materials Stock Return at time *t*,
$x_{YoYECCem(t-4)}$ is YoY Electricity Consumption of Cement sector at time (*t-4)*;
$x_{NMMEnInt(t-4)}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time (*t-4)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at the MTE market at time (*t-1).*
$x_{YoYPCO2(t-1)}$ is YoY Carbon Permits' Price variation at time (*t-1).*

Model 13: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \beta_2 x_{NMMEnInt(t-4)} + \beta_5 x_{YoYEP(t-1)} + \beta_6 x_{YoYPCO2(t-1)} + \varepsilon_t$

$Y3_t$ is YoY Chemicals Stock Return at time *t*,
$x_{YoYECChem(t-1)}$ is YoY Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{CO2Chem(t-1)}$ is the intensity of CO_2 emissions of the Chemicals (kCO2/EUR2015) at time (*t-1)*;
$x_{YoYPCO2(t-1)}$ is YoY Carbon Permits' Price variation at time (*t-1).*

Model 14: $Y3_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_4 x_{CO2Chem(t-1)} + \beta_6 x_{YoYPCO2(t-1)} + \varepsilon_t$

	(12) Basic Resources	(13) Construction & Materials	(14) Chemicals
Electricity Consumption	0.591**	-0.179	0.569**
	(0.017)	(0.280)	(0.026)
Energy Intensity value-added		0.737**	
		(0.026)	
Energy Intensity	2.250***		
	(0.001)		
CO2 Intensity			-0.549***
			(0.000)
Fwd Energy Price	0.176	-0.610***	
	(0.124)	(0.000)	
CO2 Price		0.199***	0.282***
		(0.001)	(0.000)
Constant	-0.429***	-0.276**	0.381***
	(0.000)	(0.038)	(0.000)
N	113	113	108
adj. R^2	0.185	0.249	0.372
F	9.453	10.27	22.16
p	**0.0000132*** **	**0.000000436*** **	**3.59e-11*** **
df_r	109	108	104

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year stock return of the Basic Resources sector corrected for inflation, the year-over-year stock return of the Construction & Materials sector corrected for inflation, the year-over-year stock return of the Chemicals sector correct for inflation, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the year-over-year change of the electricity consumption of the Cement sector lagged by four months, the year-over-year change of the electricity consumption of the Chemical sector lagged by one month, the physical energy intensity of Steel sector lagged by one month, the value-added energy intensity of the Non-metal Mineral sector lagged by four months, the value-added CO2 intensity of the Chemical sector lagged by one month, the year-over-year forward energy price change lagged by one month, the year-over-year carbon permits' price change lagged by one month. The Sample period: Feb 2011 – May 2020.

The table above shows considerably better inference results compared to the previous table which did not consider the forward energy price change and the carbon price change and compared to the tests on the month-over-month data.

The year-over-year changes in forward energy prices and in carbon prices are always highly significant except for the Basic Resources sector. This result is the same as for the MoM regression. This means that the Basic Resources is highly energy efficient with big volumes of production, so, the increase in the costs provoked by the fluctuations in the prices of energy and carbon is promptly mitigated, hence, the productivity remains unchanged. The adjusted R2 remains almost the same (18,5%) as in the regression with YoY electricity consumption and the physical energy intensity (17,4%): Slightly worse regression results with the CO2 intensity instead of the physical energy intensity can be found in Table 49 in Appendix C. Then, only the electricity consumption and the physical energy intensity are kept for the final YoY model of the Basic Resources sector.

As for the Construction & Materials sector, the YoY electricity consumption loses its weak significance gained in the regression with the value-added energy intensity, but the model gains a lot in terms of the predictor power (24,9% vs 4,7%) and the energy efficiency measure remains still highly significant. Construction & Materials is the most problematic sector from the point of view of energy efficiency, but it is one of the biggest in terms of output. That is why it is not surprising that the year-over-year change in electricity consumption is significant in the regressions only if combined with the ratio which translates these numbers in monetary terms for the firm (the energy consumption in relation to the production value). Needless to say, the month-over-month change in electricity consumption is much more informative in terms of production volumes and the value added and, hence, is highly statistically significant in the relative regressions. The value-added energy intensity is not significant in the month-over-month regressions relative to the Construction & Materials sector precisely because the MoM electricity consumption variable includes already all the information which it conveys. The forward energy price change is highly significant and presents the sign (negative) which is consistent with the theory. It means that it boosts the energy efficiency of the sector by impacting its productivity. The carbon price change, though, while being highly statistically significant, presents the wrong sign (positive). As it was mentioned in the theoretical part of this research, this may happen when the industrial sector is big enough to neutralise the increase of the costs by upscaling production volumes. When it not only neutralises the negative impact on productivity but increases the output more than needed (like in this case), then the sign of the coefficient of the carbon price change is reversed. The conclusion is that the YoY electricity consumption of the Cement sector corrected by the value-added energy intensity and accompanied by the YoY forward energy price change and the YoY carbon price change will be included in the final YoY model for the Construction & Materials sector.

The results relative to the YoY regression of Chemicals sector data are quite exceptional. All the variables are highly significant. The YoY electricity consumption presents the sign which is consistent with the "normal situation" in the theoretical setting of this research, but the month-over-month tests showed that the extraordinary energy efficiency of this sector changed the "normal" logics of the impacts and, thus, reversed the sign of the regression coefficient of the electricity consumption variable. It is possible to suppose that the impact of the energy efficiency measure which is statistically significant in YoY regression (the value-added CO_2 emissions intensity) was incorporated in the electricity consumption variable in the MoM regressions. In fact, in the table above it has the opposite sign with respect to the electricity consumption variable meaning that it exercises its correcting effect on it. The YoY carbon price change has the same sign (positive) as in the MoM regression which confirms the rapid response of the sector to this information in terms of transformation of the production process (either structural or energy intensive). Therefore, all the variables of the regression above: the YoY electricity consumption, the value-added CO2 intensity, the YoY carbon price change will be included in the final YoY regression for the Chemicals sector.

In conclusion, it is possible to say that the wish to replicate the study by Zhi Da (2017) brought out unanticipated results if applied to the Italian data. If used in a single-factor regression, the YoY sector electric energy variable is rarely significant in explaining the variation in sector stock prices (only if applied to the Basic Resources sector) but if it is adjusted by energy efficiency measures and the forward energy price change and the carbon price change, the inference results change considerably. The coefficient of determination increases visibly, and the electricity consumption variable may even become more significant (as for the Chemicals sector). Then, it is possible to conclude that in a study of the impact of electricity consumption on stock returns the knowledge of the energy efficiency of an energy-intensive industrial sector, combined with the availability of energy efficiency measures and the forward energy price series together with the carbon price series, is essential. However, the final check with the inclusion of financial ratios is due.

2.5. Augmented Models with Financial Variables

Finally, it is necessary to choose the financial ratios to use in the final models for the industrial sectors under consideration. For this purpose, it is necessary to combine the results of Section 2.4.1. and Section 2.4.2 with the results of Section 2.3.

For the Basic Resources industrial sector, the models that were chosen for the further analysis were the following: for the MoM data - the model in Table 37 with only the MoM electricity consumption variable (adj. R2 13,7%); for the YoY data - the model in Table 47 with the YoY electricity consumption variable and the physical energy intensity (adj. R2 = 17,4%). Then it is necessary to decide which financial ratios (B/M or P/E) should be added to the chosen model to complete it. For this industrial sector the two financial ratios cannot be used together in the regressions due to the high correlation between them (0,74), hence, they are used one at a time. Section 2.3. showed how and in which manner the industrial electricity consumption variable alone and corrected by energy efficiency measures explained the variations in sector book-to-market and price-earnings ratios. For the MoM data the percentage of explained variability of the B/M and the P/E was quite low (3,6% for the former and 4,6% for the latter). Therefore, both variables could add some information to the main model explaining stock returns, and for this purpose should be retained in the analysis. For the YoY data the percentage of explained fluctuations of B/M and P/E was somewhat higher than for the MoM tests (13,5% for the B/M and 11,6% for the P/E) but still not significant. Thus, both financial ratios should be included in the YoY final regression model of the Basic Resources sector.

For the Construction & Materials industrial sector: for the MoM data – the model in Table 44 with the MoM electricity consumption variable, the physical electricity intensity and the forward energy price change (adj. R2 = 11,1%); for the YoY data – the model in Table 48 with the YoY electricity consumption variable, the value-added energy intensity, the forward energy price change, the carbon price change (adj. R2 = 24,9%). As for the decision on the inclusion of the financial ratios: Section 2.3. showed that B/M and P/E ratios for both MoM and YoY data are not explained by the electricity consumption and the energy efficiency measures (for the MoM not explained at all, for the YoY data B/M is not explained, P/E is explained at 15,2%), hence, both ratios would be included in the final MoM and YoY models of the Construction & Materials sector to see whether they could improve their overall performance.

For the Chemicals industrial sector: for the MoM data – the model in Table 44 with the MoM electricity consumption variable, the forward energy price change, the carbon price change (adj. R2 = 8,5%); for the YoY data – the model in Table 48 with the YoY electricity consumption variable, the intensity of CO2 emissions and the carbon price change (adj. R2 = 37,2%). The situation with the financial ratios of the Chemicals sector is quite peculiar: while the MoM tests showed that the electricity consumption adjusted by energy efficiency measures could not explain the variability in sector B/M and P/E ratios, the YoY tests showed the opposite picture: the B/M market explained by 55,4% by the YoY electricity consumption corrected by CO2 intensity and P/E explained by 26,2%. Also, considering the high correlations between the CO2 intensity and the B/M ratio (0,73), and the YoY electricity consumption variable and the P/E ratio (-0,52), the two financial ratios are dropped from further analysis. The electricity consumption and the CO2 intensity already incorporate all the information that the financial ratios could contribute to the final YoY model of the Chemicals sector.

Then, it is possible to sum up the conclusion on the use of the financial ratios in the final models in the following table:

Table 50: Summary Table of percentages of Adjusted R-Squared of sector Price-Earnings and Book-to-Market ratios of Basic Resources, Construction & Materials, Chemicals sectors explained by the models with period-over-period (MoM and YoY) data and energy efficiency measures.

	B/M Max Adj. R2		**P/E** Max Adj. R2	
Basic Resources	MoM	YoY	MoM	YoY
	3,6%	13,5%	4,6%	11,6%
Use / Not Use in final model	Use	Use	Use	Use
Construction & Materials	MoM	YoY	MoM	YoY
	0%	0,2%	0%	15,2%
Use / Not Use in final model	Use	Use	Use	Use
Chemicals	MoM	YoY	MoM	YoY
	0%	55,4%	0%	26,2%
Use / Not Use in final model	Use	No	Use	No

The table describes, based on the value of the maximum adjusted coefficient of determination (Max Adj. R2) resulted from the regressions of sector Book-to-Market (B/M) ratio and sector Price-Earnings ratio (P/E) on the month-over-month and year-over-year data, which decision is reached on whether the financial variable is to be included (Use) in the final model or not (No).

Finally, the sector models personalised according to the judgement of the inclusion of the widely used financial variables (price-earnings or book-to-market ratios) were regressed with the usual OLS procedure.

2.5.1. Month-over-month data:

Table 51: OLS Regressions: MoM Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the MoM Electricity of Steel, Cement and Chemicals sectors, energy efficiency measures, forward energy price change, carbon permits' price change, sector book-to-market and price-earnings ratios.

$Y1_t$ is MoM Basic Resources Stock Return at time *t*,
$x_{MoMECS(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of Steel sector at time (*t-6*);
$x_{BMI(t-6)}$ is the Book-to-Market ratio of the Metals sector at time (*t-6);*
$x_{PEI(t-1)}$ is the Price-Earnings ratio of the Metals sector at time (*t-6).*

Model 1: $Y1_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_5 x_{BM(t-6)} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_6 x_{PE(t-6)} + \varepsilon_t$

$Y2_t$ is MoM Construction & Materials Stock Return at time *t*,
$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time (*t-3)*;
$x_{UConsC(t-3)}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time (*t-3);*
$x_{MoMEP(t-4)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-4);*
$x_{BMI(t-3)}$ is the Book-to-Market ratio of the Cement sector at time (*t-3).*
$x_{PEI(t-3)}$ is the Price-Earnings ratio of the Cement sector at time (*t-3).*

Model 3: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{UConsC(t-3)} + \beta_3 x_{MoMEP(t-4)} + \beta_5 x_{BM(t-3)} + \beta_6 x_{PE(t-3)} + \varepsilon_t$

$Y3_t$ is MoM Chemicals Stock Return at time *t*,
$x_{MoMECChem\ (t-1)}$ is MoM Seasonally Adjusted Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{MoMEP(t-5)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-5);*
$x_{MoMPCO2(t-3)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-3);*
$x_{BMI(t-1)}$ is the Book-to-Market ratio of the Chemicals sector at time (*t-1);*
$x_{PEI(t-1)}$ is the Price-Earnings ratio of the Chemicals sector at time (*t-1).*

Model 4: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\ (t-1)} + \beta_3 x_{MoMEP(t-5)} + \beta_4 x_{MoMPCO2(t-3)} + \beta_5 x_{BM(t-1)} + \beta_6 x_{PE(t-1)} + \varepsilon_t$

	Basic Resources		Construction & Materials	Chemicals
	(1)	(2)	(3)	(4)
Electricity Consumption	0.0386	0.0448	0.351***	-0.387*
	(0.855)	(0.833)	(0.000)	(0.075)
Energy Intensity			0.000718	
			(0.104)	
Fwd Energy Price			-0.167*	-0.222*
			(0.080)	(0.056)
CO2 Price				0.154**
				(0.041)
Book-Market	-0.00427		0.00310	-0.0262
	(0.836)		(0.642)	(0.376)
Price-Earnings		-0.000893	-0.00155*	0.00291
		(0.757)	(0.066)	(0.358)
Constant	-0.000796	0.0000360	-0.0693	-0.0224
	(0.971)	(0.999)	(0.176)	(0.680)
N	107	107	107	105
adj. R^2	-0.019	-0.018	0.131	0.083
F	0.0317	0.0584	4.188	2.887
p	0.969	0.943	**0.00168*** **	**0.0178** **
df r	104	104	101	99

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month stock return of the Basic Resources sector corrected for inflation, the month-over-month stock return of the Construction & Materials sector corrected for inflation, the month-over-month stock return of the Chemicals sector corrected for inflation, the month-over-month change of the electricity consumption of the Steel sector lagged by six months, the month-over-month change of the electricity consumption of the Cement sector lagged by three months, the month-over-month change of the electricity consumption of the Chemicals sector lagged by one month, the physical electricity intensity of the Cement sector lagged by three months, the month-over-month forward energy price change lagged by five months, the month-over-month forward energy price change lagged by four months, the month-over-month carbon permits' price change lagged by three months, the month-over-month carbon permits' price change lagged by one month, the book-to-market ratio of the Metals sector lagged by six months, the price-earnings ratio of the Metals sector lagged by six months, the price-earnings ratio of the Cement sector lagged by three months, the book-to-market ratio of the Cement sector lagged by three months, the book-to-market ratio of the Chemicals sector lagged by one month, the price-earnings ratio of the Chemicals sector lagged by one month. The Sample period: Feb 2010 – Dec 2018.

The results presented in the table above show that generally the financial ratios do not contribute anything to the sector MoM models explaining stock returns. All the useful information that book-to-market and price-earnings ratios contain is already contained in other variables: the electricity consumption, some energy efficiency measures, the forward energy price change and the carbon permits' price change.

It is especially true for the Basic Resources sector. The MoM electricity consumption alone is the only factor which explains the sector stock returns, and any additional regressor only worsens its performance (neither model for the Basic Resources sector in the table above is statistically significant at any acceptable level, neither regressor is significant). Therefore, the final model for this sector is the first single-factor model of Table 37: the six-months lag of the electricity consumption (EC) of the Steel sector explains 13,7% of the variation of RRR of the Basic Resources sector.

As for the Construction & Materials sector, the price-earnings ratio of the Cement sector is weakly significant in the regression, but it still manages to increase the percentage of variation of the stock returns explained by the model. Therefore, the final model for the Construction & Materials sector will be as follows: the three-months lag of the EC of the Cement sector corrected by the three-months lag of the physical electricity intensity and accompanied by the four-months lag of the forward energy price change and the three-months lag of the P/E ratio of the Cement sector explain 13,1% of the variation of RRR of the Construction & Materials sector.

The Chemicals sector is similar in results to the Basic Resources sector in what the financial ratios concern: they do not add any information to the model. Therefore, the final MoM model for the Chemicals sector is considered the one of the Table 44: the one-month lag of the EC of the Chemicals sector accompanied by the five-months lag of the forward energy price change and the three-months lag of the carbon permits' price change explain 8,5% of the variation of RRR of the Chemicals sector.

2.5.2. Year-over-Year data:

As far as the electricity consumption of the Chemicals sector together with the CO_2 intensity explain a big share of the variation of the sector B/M and P/E ratio, these financial variables were not included in the final model. Therefore, the model for the Chemicals sector with the CO_2 intensity in Table 48 is considered the final model for this sector.

Table 52: OLS Regressions: YoY Stock Returns of Basic Resources and Construction & Materials sectors against the MoM Electricity of Steel and Cement sectors, energy efficiency measures, forward energy price change, carbon permits' price change, sector book-to-market and price-earnings ratios.

$Y1_t$ is YoY Basic Resources Stock Return at time *t*,
$x_{YoYECS(t-1)}$ is YoY Electricity Consumption of Steel sector at time (*t-1*);
$x_{UConsS(t-1)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (kWh/t) at time (*t-1*);
$x_{BMI(t-1)}$ is the Book-to-Market ratio of the Metals sector at time (*t-1*);
$x_{PEI(t-1)}$ is the Price-Earnings ratio of the Metals sector at time (*t-1*).

Model 1: $Y1_t = \beta_0 + \beta_1\, x_{YoYECS(t-1)} + \beta_3\, x_{UConsS(t-1)} + \beta_6\, x_{BM(t-1)} + \varepsilon_t$

Model 2: $Y1_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_3 x_{UConsS(t-1)} + \beta_7 x_{PE(t-1)} + \varepsilon_t$

$Y2_t$ is YoY Construction & Materials Stock Return at time *t*,
$x_{YoYECCem(t-4)}$ is YoY Electricity Consumption of Cement sector at time (*t-4)*;
$x_{NMMEnInt(t-4)}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time (*t-4)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at the MTE market at time (*t-1);*
$x_{YoYPCO2(t-1)}$ is the YoY Carbon Permits' Price variation at time (*t-1);*
$x_{BMI(t-4)}$ is the Book-to-Market ratio of the Cement sector at time (*t-4).*
$x_{PEI(t-4)}$ is the Price-Earnings ratio of the Cement sector at time (*t-4).*

Model 3: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem(t-4)} + \beta_2 x_{NMMEnInt(t-4)} + \beta_4 x_{YoYEP(t-1)} + \beta_5 x_{YoYPCO2(t-1)} + \beta_6 x_{BM(t-4)} + \beta_7 x_{PE(t-4)} + \varepsilon_t$

	Basic Resources		Construction & Materials
	(1)	(2)	(3)
Electricity Consumption	0.672**	0.508	0.0714
	(0.050)	(0.126)	(0.767)
Energy Intensity value added			0.946**
			(0.012)
Energy Intensity	1.125	1.366	
	(0.154)	(0.106)	
Fwd Energy Price			-0.565***
			(0.000)
CO2 Price			0.190***
			(0.001)
Book-Market		0.0113	-0.0564***
		(0.833)	(0.005)
Price-Earnings	0.0125*		-0.0105***
	(0.089)		(0.000)
Constant	-0.272**	-0.262*	-0.129
	(0.046)	(0.061)	(0.390)
N	96	96	96
adj. R^2	0.056	0.027	0.406
F	2.896	1.869	11.82
p	0.0394	0.140	1.04e-09
df_r	92	92	89

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year stock return of the Basic Resources sector corrected for inflation, the year-over-year stock return of the Construction & Materials sector corrected for inflation, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the year-over-year change of the electricity consumption of the Cement sector lagged by four months, the physical electricity intensity of the Cement sector lagged by four months, the year-over-year forward energy price change lagged by one month, the year-over-year carbon permits' price change lagged by one month, the book-to-market ratio of the Metals sector lagged by one month, the price-earnings ratio of the Metals sector lagged by one month, the price-earnings ratio of the Cement sector lagged by four months, the book-to-market ratio of the Cement sector lagged by four months. The Sample period: Jan 2011 – Dec 2018.

Judging by the results in the table above, the only industrial sector whose model is improved after the inclusion of the financial ratios is the Construction & Materials sector, the least performing sector from the point of view of energy efficiency. In fact, this sector presents an anomaly because its earnings grow faster than the productivity deducted from the electricity usage. That is why the financial ratios which are based on the effective productivity of the sector, not necessarily linked to the increase or reduction in electricity consumption, make their important contribution to the sector YoY model.

For the other sectors (Basic Resources and Chemicals), the information which is incorporated in the B/M and P/E ratios is already present in the electricity consumption variable, some energy efficiency measures and the price changes of energy and carbon emissions. In fact, the price-earnings ratio of the Steel sector reduces the significance of the electricity consumption variable by attracting towards itself a little of the statistical significance. By doing so it also reduces the performance of the model which is decreased. Therefore, to get the best inference results, these financial ratios should be dropped from the models for Basic Resources and Chemicals sectors. This is true for both month-over-month and year-over-year tests.

Also, as it was expected, the energy efficiency measures add significance to the models unevenly across the sectors. It can be explained not only by the energy efficiency situation of the sectors but also by some individual production decisions of the firms that cannot be forecasted beforehand and are based on a variety of factors which are found outside the production process.

So, to sum up, the final most successful models which result from the analysis of this chapter the from the point of view of predictor power are the following:

Table 53: Synthetic representation of the judgment on final regression results on MoM and YoY data of Basic Resources, Construction & Materials and Chemicals sectors stock returns, electricity consumption of Metals, Cement and Chemicals sectors, energy efficiency measures, forward energy price, carbon price, sector book-to-market and price-earnings ratios.

	Basic Resources MoM	Basic Resources YoY	Construction & Materials MoM	Construction & Materials YoY	Chemicals MoM	Chemicals YoY
Electricity Consumption	✓	✓	✓	✓	✓	✓
Energy Intensity value added	x	x	x	✓	x	x
Energy Intensity	x	✓	✓	x	x	x
CO2 Intensity	x	x	x	x	x	✓
Fwd Energy Price	x	x	✓	✓	✓	x
CO2 Price	x	x	x	✓	✓	✓
B/M	x	x	x	✓	x	x
P/E	x	x	✓	✓	x	x
Adj R2	**13,7%**	**17,4%**	13,1%	40,6%	**8,5%**	**37,2%**

The table describes the results of the OLS regressions performed on the following variables: the month-over-month and the year-over-year stock returns of the Basic Resources sector corrected for inflation, the month-over-month and the year-over-year stock return of the Construction & Materials sector corrected for inflation, the month-over-month and the year-over-year stock return of the Chemicals sector corrected for inflation, the month-over-month change of the electricity consumption of the Steel sector lagged by six months, the month-over-month change of the electricity consumption of the Cement sector lagged by three months, the month-over-month change of the electricity consumption of the Chemicals sector lagged by one month, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the year-over-year change of the electricity consumption of the Cement sector lagged by four months, , the physical electricity intensity of the Cement sector lagged by three and four months, the month-over-month forward energy price change lagged by four and by five months, , the year-over-year forward energy price change lagged by one month, the month-over-month carbon permits' price change lagged by one and by three months, , the year-over-year carbon permits' price change lagged by one month, the book-to-market ratio of the Metals sector lagged by one and by six months, the price-earnings ratio of the Metals sector lagged by one and by six months, the price-earnings ratio of the Cement sector lagged by three and by four months, the book-to-market ratio of the Cement sector lagged by three and by four months, the book-to-market ratio of the Chemicals sector lagged by one month, the price-earnings ratio of the Chemicals sector lagged by one month. The Sample period for MoM: Feb 2010 – Dec 2018, for YoY: Jan 2011 – Dec 2018.

The conclusion that it is possible to draw from the analysis of this chapter is that the electricity consumption variable corrected, if needed, by the energy efficiency measures and accompanied by the boosters of energy efficiency (the forward energy price change and the carbon price change) is enough to explain an important share of the variation of sector stock returns. And the financial variables (B/M and P/E) which are commonly used in asset pricing practices, lose their predictor power and worsen the model inference results if included in the tests on the relatively energy efficient industrial sectors (Basic Resources and Chemicals) together with the electricity consumption and the other abovementioned variables.

The Construction & Materials sector, which is the least energy efficient sector out of the three sectors under consideration (and the least but one "worst" sector among all industrial sectors in Italy, the least being the Machinery sector) needs numerous predictors of stock returns in its model because the electricity consumption variable alone is not enough to explain the fluctuations in the sector price index (MoM and YoY change). It is evident that the market does not fully trust the data on electricity consumption to value the productivity of this sector. Therefore, it needs other information to deduce the sector growth potential.

The results presented in this chapter can be considered important and reliable. The only minus is the narrowness of the dataset due to the availability. Hence, if the same tests performed on the data coming from a different country with a similar market produce the same results, the robustness of the research would gain weight. So, for this purpose the Swedish data were gathered and tested. The next chapter presents the relative results.

Chapter 3. The Swedish Data

In order to enrich and confirm the study on the Italian industrial sectors which does not present large datasets, the only way is to find the data relative to a country with a similar market and, most importantly, with available detailed data on sector energy consumption and energy efficiency measures.

Sweden happens to have a stock market similar to the Italian one in terms of market capitalization (2023 data: 704 997,6 ml € for Borsa Italiana, 793 360 ml € (converted from Swedish Korona) for Stockholm Stock Exchange) and number of listed companies (425 for Italy vs 395 for Sweden). Besides, the industrial sectors under consideration (Basic Resources, Construction & Materials, Chemicals) have a similar composition for both countries: the least represented is the Chemicals sector (1-2 companies) which is followed by the Basic Resources sector (4-8 companies) and, finally, the most represented is the Construction & Materials sector (13-20 companies). Also, the Construction & Materials sector is again the least virtuous in terms of energy efficiency which grows very little during the sample period (see the comparative Figures 19, 22 and 23 in Appendix A) while Chemicals (the Italian Chemicals sector presents a clearer and more regular trend, see Figure 20 and 25 in Appendix A) and Basic Resources sectors (similar decreasing trends for both countries, see Figure 18, 21 and 24 in Appendix A) are much more performing in this respect. The website of Odyssee-Mure project does not provide the energy efficiency index ODEX for Sweden but knowing that it is mostly based on the physical energy intensity of the industrial sectors, it is possible to deduct the information which it usually conveys from the energy efficiency measures. Besides, Odyssee-Mure project issues regularly the country energy profiles[21] which help to understand the undergoing improvements due to energy efficiency policies.

The database on industrial electricity consumption in Sweden is rich, up-to-date and freely available on the website of Statistics Sweden[22]. For the purposes of the analysis of this research those data were then transformed into MoM and YoY time-series, and in the first case also seasonally adjusted with the Demetra software.

The series of monthly average prices of Swedish industrial sector stock indices were downloaded from www.investing.com website and then converted into MoM and YoY time-series.

Unfortunately, the part of the regressions including the energy forward price and the carbon permit

[21] https://www.odyssee-mure.eu/publications/efficiency-trends-policies-profiles/

[22] https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__EN__EN0108/ElForbr07M/

price could be performed only partially lacking any information on the carbon permits' price (Sweden's energy certificates market has been inactive since 2008 due to the lack of demand). The data on the sector price-earnings ratio and sector book-to-market ratios are unavailable either. However, the first part of the analysis may still contribute significantly by serving as a proof of the results obtained by the main study based on the Italian data.

As in the previous chapter, this part of the study begins with the month-over-month data regressions and then goes on with the year-over-year ones.

3.1. Data and Methodology.

3.1.1. Data.

Swedish industrial energy consumption historical data (Gwh) for the period between 2009 and 2021 (January 2009 – October 2021) was downloaded from the Statistics Sweden website. The data are monthly electric energy supply statistics (GWh) referring to three energy-intensive Swedish industrial sectors (Construction & Materials; Chemicals; Basic Resources). The list of the Swedish companies whose electricity consumption is considered by the database, is not available.

The time-series of price indices that constitute the dependent variables in the statistical tests (Swedish stock returns) were downloaded once again from the website www.investing.com. The market-value-weighted OMX Stockholm stock market subindices were associated with the industrial sector electricity consumption series which have the same name:

Table 54: Matching of Stock Market Indices to Industrial Electricity Consumption by sector.

Stock Market Index	Sector Electricity Consumption
OMX Stockholm Basic Resources PI SX5510PI	Steel & Metals (24 stal- och metallverk)
OMX Stockholm Construction & Materials PI SX5010PI	Non-metallic Mineral (23 industri för andra icke-metalliska mineraliska produkter)
OMX Stockholm Chemicals PI SX1350PI	Chemicals & Petroleum products (19-21 kemisk industri, petroleumprodukter och läkemedelsindustri)

Table 55: Descriptive Statistics (investing.com)

The table gives a detailed descriptive statistics of the data downloaded from the website investing.com

Index Name	Code	Stock Exchange	Currency	Time Frame	Period	Price Type
OMX Stockholm Basic Resources PI	SX5510PI	Stockholm	SEK	Monthly	Jan 2009 – Oct 2021	Last Price avg
OMX Stockholm Construction & Materials PI	SX5010PI	Stockholm	SEK	Monthly	Jan 2009 – Oct 2021	Last Price avg
OMX Stockholm Chemicals PI	SX1350PI	Stockholm	SEK	Monthly	Jan 2009 – Oct 2021	Last Price avg

A time varying energy intensity, or energy efficiency, is included in the theoretical model which was previously tested for the Italian data and now will be tested for the Swedish data. All the necessary Swedish energy-efficiency measures were downloaded from Odyssee Mure project website[23]. And specifically: the Primary Metals (ISIC 24) Energy Intensity (koe/EUR2015); the Intensity of CO_2 emissions of the Steel industry (tCO_2/t); the Specific Energy consumption of the Steel industry; the Non-Metallic Minerals (ISIC 23) Energy Intensity at exchange rate (koe/EUR2015); the Intensity of CO_2 emissions of the Cement industry (electricity included) (tCO_2/t); the Specific Electricity consumption of the Cement industry (kWh/t); the Chemical Industry (ISIC 20-21) value-added Energy Intensity (koe/EUR2015); the value-added total CO_2 Intensity of the Chemical industry (kCO_2/ EUR2015). All the energy-efficiency data are at annual level.

The details on the calculation of the energy efficiency measures downloaded from the investing.com website are the same for Italy and for Sweden and can be found in Table 16.

These measures were associated with the industrial sector electricity consumption provided by Statistics Sweden in the following way:

[23] https://www.odyssee-mure.eu/.

Table 56: Matching of Energy Efficiency Measures to Industrial Electricity Consumption by sector

Energy Efficiency Measure	Sector Electricity Consumption
Primary Metals (ISIC 24) Energy Intensity CO2 emissions of Steel per ton Unit Energy consumption of Steel	Steel & Metals (24 stal- och metallverk)
Non-Metallic Mineral (ISIC 23) Energy Intensity CO2 emissions of Cement per ton Unit Electricity consumption of Cement	Non-metallic Mineral (23 industri för andra icke-metalliska mineraliska produkter)
Chemical industry (ISIC 20-21) Energy Intensity CO2 emissions Intensity of Chemical industry	Chemicals & Petroleum products (19-21 kemisk industri, petroleumprodukter och läkemedelsindustri)

The descriptive statistics of the data downloaded from the Odyssee-Mure database for Swedish industry are the same as for the Italian industry and can be found in Table 19.

The list of the used energy intensity measures was presented above in Table 56. Once again, the data are available only at annual level; therefore, the monthly series were produced artificially by Denton procedure in Stata which recreates the monthly fluctuations of the annual data by adapting the trend from the time-series of a variable which is correlated with the variable under consideration. The indicator for this purpose was the variable price of electricity in Sweden (Rörligt pris), whose historical monthly series (2008 – 2023) is published by the Swedish Energy Markets Inspectorate (Energimarknadsinspektionen)[24].

The table below shows the correlations between energy efficiency measures and the variable electricity price in Sweden. The values are positive (except for the value-added energy intensity of the Chemicals sector) and most of them are reasonably high for the variable electricity price to be considered the indicator for the Denton temporal disaggregation method. Only the value-added energy intensity of the Chemicals sector presents negative and not significant correlation with the electricity price time-series.

[24] https://ei.se/ Energimarknadsinspektionen, the Swedish Energy Markets Inspectorate.

Table 57: *Correlation between energy and CO2 emissions intensities and the Swedish Variable Electricity Price (Rörligt pris)*

	Energy efficiency measures							
	Energy intensity of Primary Metals (koe/EUR 2015)	Unit consumption of crude steel (toe/t)	Total CO2 emissions of steel per ton (tCO2/t)	Energy intensity of non-metallic minerals (koe/EUR2015)	Unit consumption of electricity of Cement (kWh/t)	Total CO2 emissions of cement per ton (tCO2/t)	Energy intensity of Chemicals (koe/EUR2015)	Total CO2 intensity of Chemicals (kCO2/EUR2015)
Variable Electricity Price (öre/KWh)	0,30	0,61	0,77	0,62	0,56	0,36	-0,21	0,52

The monthly data on Swedish forward energy prices were downloaded from the official website of the Swedish Energy Markets Inspectorate (https://ei.se/). The data were time series of fixed prices contracts for one and three years, the average price of these contracts was used to create a monthly time-series of forward energy price. Then the series was transformed into MoM and YoY series according to the necessity, and, if seasonality was present (MoM series), it was then removed by the Tramo-Seats procedure by means of Demetra+ software.

The monthly data on the Swedish inflation index (HICP, Overall Harmonised Index of Consumer Prices[25], not seasonally adjusted, monthly values, 2015=100), necessary for the calculation of the real stock return (RRR = (1 + stock return)/(1 + inflation) -1), were once again downloaded from the website of the Statistical Data Warehouse of the European Central Bank. Monthly data (levels) for the period Jan 2008 – Jan 2023. Then, the MoM and YoY series were produced manually on the basis of the levels series. The stock return series used for the calculation of the RRR was either in MoM, not seasonally adjusted, or in YoY form.

3.1.2. Methodology

The main reference for the methodology of this part of the research remains the same as for the Italian data (equation 50) - the first specification of technology in Burnside et al. (1995): the non-substitutability of the energy input by other inputs; and the year-over-year growth rate by Da et al. (2017).

[25]https://sdw.ecb.europa.eu/quickview.do;jsessionid=29B15E1DC261F6D28E38698557200035?SERIES_KEY=122.ICP.M.SE.N.000000.4.INX

The raw industrial electricity consumption time-series downloaded from the Statistics Sweden website are affected by seasonality which could produce unreliable inference results. Then, as already pointed out, the raw data were first tested for seasonality by the Demetra+[26] software and then seasonally adjusted. Finally, only the seasonally adjusted time-series were used in the regressions. The electricity consumption variable is again used as a lagged variable in the regressions. The justification is the same as for the Italian data – the different length of production cycles and different company decisions on the productivity (production capacity), products etc.

The annual Odyssee-Mure energy efficiency measures relative to the Swedish energy-intensive industrial sectors, which have undergone the Denton procedure (the Swedish variable energy price being the indicator) to obtain monthly time-series, as for the Italian data, were lagged according to the chosen lag of the electricity consumption variable for each sector under consideration.

As for the Italian data, the check for the possible multicollinearity issue between the annual series of the energy intensities of the same industrial sectors is due.

Without doubt, the series of energy efficiency measures which are correlated to the same indicator, are correlated between themselves too. So, the correlations matrix for the monthly data of the energy efficiencies was omitted. Only the correlations between the annul data are presented in the table below.

Table 58: *Correlations check between the energy intensities of the Swedish energy-intensive industrial sectors.*

Correlations ↓→	*Energy Intensity of* ***Primary Metals*** *(koe/EUR2015)*	*Energy Intensity of* ***Non-Metallic Minerals*** *(koe/EUR2015)*
Energy Intensity of ***Steel*** *(toe/t)*	**0,84**	
Electricity Intensity of ***Cement*** *(kWh/t)*		**0,63**

For the **Steel** sector: correlation between the unit consumption of energy per ton of product of crude steel (toe/t) and the energy intensity of Primary Metals sector (koe/EUR2015). For the **Cement** sector: correlation between the unit consumption of electricity per ton of product (kWh/t) and the energy intensity of Non-Metallic Minerals sector (koe/EUR2015). Sample Period: 2009 – 2020.

[26] The TRAMO-SEATS procedure.

Besides, as for the Italian data, also for the Swedish data the intensity of CO_2 emissions is checked for being a proxy for the electricity consumption of the Swedish industrial energy-intensive sectors. For Sweden too the correlations between the energy (electricity) intensity and the CO_2 emissions intensity are positive and noteworthy:

Table 59: *Correlations check between the energy intensities and CO2 emissions intensity of the energy-intensive industrial sectors.*

Correlations ↓→	*CO2 Intensity of* ***Steel*** *(tCO2/t)*	*CO2 Intensity of* ***Chemicals*** *(kCO2/EUR2015)*	*CO2 Intensity of* ***Cement*** *(tCO2/t)*
Energy Intensity of ***Steel*** *(toe/t)*	**0,96**		
Energy Intensity of ***Primary Metals*** *(koe/EUR2015)*	**0,68**		
Energy Intensity of ***Chemicals*** *(koe/EUR2015)*		**0,68**	
Electricity Intensity of ***Cement*** *(kWh/t)*			**0,45**
Energy Intensity of ***Non-Metallic Minerals*** *(koe/EUR2015)*			**0,31**

For the **Steel** sector: correlation between the unit consumption of energy per ton of product of crude steel (toe/t), the energy intensity of Primary Metals sector (koe/EUR2015) and the intensity of CO2 emissions of steel production per ton of product (tCO2/t). For the **Chemical** sector: correlation between the energy intensity per 1€ (base 2015) of production value (koe/EUR2015) and the intensity of CO2 emissions of chemical production per 1€ (base 2015) of production value (kCO2/EUR2015). For the **Cement** sector: correlation between the unit consumption of electricity per ton of product (kWh/t), the energy intensity of Non-Metallic Minerals sector (koe/EUR2015) and the intensity of CO2 emissions of cement production per ton of product (tCO2/t). Sample Period: 2009 - 2020.

Therefore, just like for the Italian data, the intensity of CO_2 emissions is added to the regression equations together with energy intensities.

Again, the full version of the equation (50) could never be performed and only reduced versions were tested due to the high correlation between the energy efficiency measures.

As for the Italian data, the Swedish forward energy price change variable was used in its lagged version to account for the delay with which the sector reacts to its variation in terms of energy efficiency.

The steps of the analysis are identical to the ones carried out on the Italian data. Therefore, first the regressions with MoM data series were performed (the dependent variable being the MoM sector stock return, the independent variable – MoM sector electricity consumption variable). First, to decide which lag (from one month to six months) of the electricity consumption variable to use, the single-factor regressions were performed. Then, the most statistically significant lag was used in multiple-factor regressions with energy efficiency measures. After having chosen the most significant energy efficiency measure, if any, it is then used in the final regression with the Swedish forward energy price change.

Once again by following the methodology by Zhi Da et al. (2017) the regression tests (the OLS procedure, the ordinary least squares) were carried out on the year-over-year time-series to see whether the results are comparable with those obtained by Zhi Da et al. for the US stock market and those obtained for the Italian data in this research. The monthly YoY sector stock return acts as the dependent variable in the regression where the independent variable is the monthly YoY sector electricity consumption growth, the energy efficiency measures and the Swedish forward energy price change. The steps are the same as for the tests on the MoM data.

After having performed the tests on MoM and YoY, the conclusions are drawn whether also for the Swedish energy-intensive industrial sectors the electricity consumption, corrected by energy efficiency measures, explains the relative stock returns.

3.2. Regressions

Here follows is the regression analysis performed on the electricity consumption, energy efficiency measures and the forward energy price change, the dependent variable being the month-over-month or the year-over-year change in industrial sector stock returns corrected for inflation.

The results would be again analised from the perspective of the relation between electricity consumption and the change in energy efficiency – the crucial point in the chain of impacts which goes through productivity and up to stock prices and stock returns.

As it was mentioned at the beginning of this chapter, the Construction & Materials sector (Non-Metallic Minerals, Cement) is the least performing from the point of view of energy efficiency for both Italy and Sweden (Figures 19, 22, 23 in Appendix A). Hence, it is expected that the regression results on the Swedish data would be similar to those obtained for Italy. In turn, the Swedish Chemicals sector is more energy efficient than the Italian one but the speed of improvement of energy efficiency in the sample period is higher for Italy (Figures 20 and 25 in Appendix A). The decreasing trend of energy efficiency measures for the Swedish Chemicals sector is not clear, it has high oscillations and sometimes even reverses the direction of movement. Hence, it is plausible to expect slightly worse regression results compared to those of the tests on the Italian data. The Swedish Basic Materials sector (Primary Metals, Steel) seems to be more or less equally energy-efficiency performing (Figures 18, 21, 24 in Appendix A) as the corresponding Italian sector. Therefore, the expected regression results are not expected to differ greatly from those of the Italian data.

The following tests will show if these intuitions are correct.

3.2.1. Month-over-month data

The first step of the MoM regressions is the same as for the Italian MoM data: the choice of the most significant lag of the electricity consumption variable of the energy-intensive sectors under consideration to be used in further analysis. The relative tables can be found in Appendix B: for the Swedish Basic Resources sector – Table 66, for the Swedish Construction & Materials sector – Table 67, for the Swedish Chemicals sector – Table 68.

As before, the energy efficiency measures are used one at a time in the regressions due to high correlations between them (see Appendix B).

Then, the analysis goes on with the regression of MoM sector stock returns on the chosen lag of the electricity consumption variable and energy efficiency measures.

Table 72: OLS Regressions: MoM Stock Returns of Swedish Basic Resources, Construction & Materials and Chemicals sectors against their MoM Electricity Consumption and energy efficiency measures.

$Y1_t$ is MoM Swedish Basic Resources Stock Return at time t,
$x_{MoMECS(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Basic Resources sector at time (*t-3)*;
$x_{PMEnInt(t-3)}$ is the Energy intensity of Primary Metals sector (koe/EURO 2015) at time (*t-3)*;
$x_{UConsS(t-3)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-3)*;
$x_{CO2Steel(t-3)}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time (*t-3)*.

Model 1: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \varepsilon_t$

Model 2: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \beta_2 x_{PMEnInt(t-3)} + \varepsilon_t$

Model 3: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \beta_3 x_{UConsS(t-3)} + \varepsilon_t$

Model 4: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \beta_4 x_{CO2Steel(t-3)} + \varepsilon_t$

$Y2_t$ is MoM Swedish Construction & Materials Stock Return at time t,
$x_{MoMECCem(t-4)}$ is MoM Seasonally Adjusted Electricity Consumption of Construction & Materials sector at time (*t-4)*;
$x_{NMNEnInt(t-4)}$ is the Energy intensity of Non-Metal Minerals sector (koe/EURO 2015) at time (*t-4)*;
$x_{UConsC(t-4)}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time (*t-4)*;
$x_{CO2Cement(t-4)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-4)*.

Model 5: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \varepsilon_t$

Model 6: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \beta_2 x_{NMMEnInt(t-4)} + \varepsilon_t$

Model 7: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \beta_3 x_{UConsC(t-4)} + \varepsilon_t$

Model 8 : $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \beta_4 x_{CO2Cement(t-4)} + \varepsilon_t$

$Y3_t$ is MoM Swedish Chemicals Stock Return at time *t*,
$x_{MoMECChem(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of Chemical sector at time (*t-6)*;
$x_{ChemEnInt(t-6)}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time (*t-6)*;
$x_{CO2Chem(t-6)}$ is the Intensity of CO2 emissions of Chemicals sector (kCO_2/EURO 2015) at time (*t-6)*.

Model 9: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-6)} + \varepsilon_t$

Model 10: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-6)} + \beta_2 x_{ChemEnInt(t-6)} + \varepsilon_t$

Model 11: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-6)} + \beta_4 x_{CO2Chem(t-6)} + \varepsilon_t$

	Basic Resources Sweden				Construction & Materials Sweden				Chemicals Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	0.345**	0.347**	0.421***	0.427***	0.136*	0.139*	0.126*	0.124*	0.492**	0.498**	0.494**
	(0.015)	(0.020)	(0.004)	(0.004)	(0.066)	(0.061)	(0.084)	(0.090)	(0.029)	(0.027)	(0.030)
Energy Intensity value added		0.00550				-0.114				-0.850	
		(0.829)				(0.266)				(0.325)	
Energy Intensity			-0.275**				-0.000528*				
			(0.017)				(0.058)				
CO2 Intensity				-0.0984**				-0.213*			-0.0955
				(0.010)				(0.050)			(0.870)
Constant	0.00663	0.00508	0.0884**	0.0967***	0.0113***	0.0336	0.0714**	0.0595**	0.0206***	0.0624	0.0271
	(0.212)	(0.624)	(0.011)	(0.006)	(0.008)	(0.101)	(0.028)	(0.020)	(0.006)	(0.148)	(0.511)
N	153	143	143	143	138	138	131	131	132	132	131
adj. R^2	0.032	0.027	0.066	0.072	0.017	0.019	0.034	0.036	0.029	0.029	0.021
F	6.050	2.987	5.982	6.503	3.426	2.340	3.278	3.402	4.879	2.928	2.426
p	**0.015****	0.0537*	**0.0032****	**0.00199*****	0.066*	0.10*	**0.0409****	**0.0363****	**0.0289****	0.0571*	0.0924*
df_r	151	140	140	140	136	135	128	128	130	129	128

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Basic Resources stock return corrected for inflation, the month-over-month Swedish Construction & Materials stock return corrected for inflation, the month-over-month Swedish Chemicals stock return corrected for inflation; the month-over-month electricity consumption of Basic Resources sector lagged by three months, the month-over-month electricity consumption of Construction & Materials sector lagged by four months, the month-over-month electricity consumption of Chemicals sector lagged by six months, and the energy efficiency measures: the value-added energy intensity of Primary Metals sector lagged by three months, the physical energy intensity of Steel sector lagged by three months, the physical CO2 emissions intensity of Steel sector lagged by three months, the value-added energy intensity of Non-metal Minerals sector lagged by four months, the physical electricity intensity of Cement sector lagged by four months, the physical CO2 emissions intensity of Cement sector lagged by four months, the value-added energy intensity of Chemicals sector lagged by six months, the value-added CO2 emissions intensity of Chemicals sector lagged by six months. Max Sample period: Feb 2009 – Jul 2020.

First of all, it is important to highlight the fact that the results presented in the table above confirm once again the base of the theoretic model elaborated in this research - namely, the predictor power of the industrial electricity consumption over the industrial sector stock returns (by impacting the productivity). The chosen lags of sector month-over-month electricity consumption variable are always statistically significant if used alone (models 1, 5, 9). The sign (positive) of the coefficient of the EC variable for industrial sectors is consistent with the model setting. This time it is true also for the electricity consumption of the Chemicals sector which presented a negative sign in the MoM regressions on the Italian data. This is exactly what was expected judging by the energy efficiency of the Swedish industrial sectors. The energy efficiency of the Swedish Chemicals sector does not grow at such an extraordinary rate as it does in Italy, therefore, the increase in the usage of electricity is more important for the productivity than the increase, if there is any, of the sector energy efficiency. Hence, the sign of the coefficient is not reversed, and the logic of impacts follows the theoretical setting of this research.

As for the signs of the regression coefficients of the energy efficiency measures, some seeming anomalies are observed. The expected sign (positive) is not detected for any sector. This means that the increase in electricity consumption leads to the increase in energy intensities (energy and CO2 per ton of production), and consequently the decrease in energy efficiency that in theory should lead to the decrease in production. However, it is clear from the positive sign of the electricity consumption that the production increases. Then, it is evident that the production increase is less proportional than the increase in energy input and the relative CO2 emissions. So, in the end the energy/CO2 intensities increase, and the energy efficiency is slightly decreasing. This fact justifies the negative sign of energy efficiency measures.

Besides, if for the Italian data the energy efficiency measures were never statistically significant for the Basic Resources and Chemicals sectors, here the physical energy intensity and the CO2 intensity are significant for the Basic Resources sector. However, the Chemicals sector, as before, does not need the correcting effect of any energy efficiency measure which are not significant. For the Construction & Materials sector the physical energy intensity and the CO2 intensity are again significant.

It is important to note that the market relies more on the continuous upward change in energy efficiency which ensures a growth potential of the sector. The Chemicals sector shows some important oscillations in energy/CO2 intensities at monthly level (Figures 20 and 25), hence, the market prefers to rely entirely on the data on electricity consumption. The Construction & Materials sector presents an unclear situation: Figure 19 shows high fluctuations in the value-added energy intensity which is difficult to interpret for the market, Figures 22 and 23 show smooth but ambiguous trends in the oscillations of the energy and CO2 intensities, hence the market pays slight attention to them (the variables are weakly significant in the regressions). Therefore, the market still relies more on the electricity usage variable rather than on the energy efficiency measures to value the growth potential of the sector.

For the Basic Resources sector too the impact of the electricity consumption is more important for the explanation of stock returns rather than the change in energy efficiency. The speed of the increase in energy efficiency (Figures 18, 21, 24) is not fast enough (in fact, the trend is rather flat) to impact the productivity in the way for the market to notice that before taking the decision on the reliability of the firms of this industrial sector.

Then, it is necessary to choose the energy efficiency measures which will be retained in further analysis. For the Basic Resources sector the most performing intensity is the CO2 emissions intensity. Therefore, it will be included in further regressions. For the Construction & Materials sector the most significant measure is again the CO2 emissions intensity. Keeping in mind that the annual series on CO2 emissions of the Cement sector was not highly correlated (0,36) with the indicator series used to produce monthly series, it will be included in the further analysis with some precautions.

So, before moving to the tests on year-over-year, the second step of the analysis of the month-over-month data should be performed. It consists in integrating the regression analysis with the forward electricity price change. The lags of this variable are chosen in such a way as to produce the best inference results (see Tables 69, 70, 71 in Appendix C). Then, the multiple-factor regressions are run.

Table 73: OLS Regressions: MoM Stock Returns of Swedish Basic Resources, Construction & Materials and Chemicals sectors against their MoM Electricity Consumption, energy efficiency measures and forward energy price change.

$Y1_t$ is MoM Swedish Basic Resources Stock Return at time *t*,
$x_{MoMECS(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Basic Resources sector at time (*t-3)*;
$x_{CO2Steel(t-3)}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time (*t-3)*;
$x_{MoMEP(t-3)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at time (*t-3).*

Model 12: $Y1_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \beta_2 x_{CO2Steel(t-3)} + \beta_3 x_{MoMEP(t-3)} + \varepsilon_t$

$Y2_t$ is MoM Swedish Construction & Materials Stock Return at time *t*,
$x_{MoMECCem(t-4)}$ is MoM Seasonally Adjusted Electricity Consumption of Construction & Materials sector at time (*t-4)*;
$x_{CO2Cement(t-4)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-4)*;
$x_{MoMEP(t-4)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at time (*t-4).*

Model 13: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \beta_2 x_{CO2Cement(t-4)} + \beta_3 x_{MoMEP(t-4)} + \varepsilon_t$

$Y3_t$ is MoM Swedish Chemicals Stock Return at time *t*,
$x_{MoMECChem\,(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of Chemical sector at time (*t-6)*;
$x_{MoMEP(t-1)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at time (*t-1).*

Model 14: $Y3_t = \beta_0 + \beta_1 x_{MoMECChem\,(t-6)} + \beta_3 x_{MoMEP(t-1)} + \varepsilon_t$

	(12) Basic Resources Sweden	(13) Construction & Materials Sweden	(14) Chemicals Sweden
Electricity Consumption	0.430***	0.126*	0.430*
	(0.004)	(0.085)	(0.055)
CO2 Intensity	-0.0905**	-0.189*	
	(0.023)	(0.094)	
Fwd Energy Price	-0.0786	-0.0695	0.305**
	(0.481)	(0.442)	(0.037)
Constant	0.0891**	0.0539**	0.0219***
	(0.016)	(0.043)	(0.003)
N	143	131	132
adj. R^2	0.069	0.033	0.054
F	4.486	2.459	4.716
p	**0.00488*** **	0.0658*	**0.0105** **
df_r	139	127	129

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month stock return of the Swedish Basic Resources sector corrected for inflation, the month-over-month stock return of the Swedish Construction & Materials sector corrected for inflation, the month-over-month stock return of the Swedish Chemicals sector corrected for inflation, the month-over-month change of the electricity consumption of the Basic Resources sector lagged by three months, the month-over-month change of the electricity consumption of the Construction & Materials sector lagged by four months, the month-over-month change of the electricity consumption of the Chemicals sector lagged by six months, the physical electricity intensity of the Cement sector lagged by three months, the physical CO2 emissions intensity of Steel sector lagged by three months, the physical CO2 emissions intensity of Cement sector lagged by four months, the month-over-month forward energy price change lagged by one, three and four months. The Sample period: Feb 2009 – Jul 2020.

As it can be seen from the results in the table above the month-over-month change in electricity consumption is confirmed to be an important predictor of industrial sector stock returns. However, the addition of the forward energy price change to the regression does not improve the performance of the model where the energy efficiency measures are present. On the other hand, if used with the electricity consumption of the Chemicals sector, it becomes statistically significant and improves the performance of the whole model. This is consistent with the idea that the forward energy price may work like a booster but this time not of energy efficiency, which is stagnant, but directly of productivity through the increase of energy input. The increase in future price of energy makes the companies decide to produce more today rather than tomorrow to mitigate the future cost or they may even change the product type. Therefore, the market notices the increase in productivity and values it positively. Hence, the positive regression coefficient sign.

If instead of the CO2 intensity, the physical energy intensities are used in the regressions for Basic Resources and Construction & Materials sectors, the results are getting a little bit worse (see Table

74 in Appendix C). The useful information, which they could convey to the model, is already present inside the electricity consumption variable, hence, adding them to the regression only injects some volatility which worsens the inference results because the market does not base its valuation decisions on it.

Then, the final MoM models for the explanation of Swedish stock returns of the Swedish industrial sectors will be the following: for the Basic Resources – the MoM electricity consumption of the Basic Resources sector and the CO2 intensity of the Steel sector; for the Construction & Materials sector – the MoM electricity consumption of the Construction & Materials sector and the CO2 intensity of the Cement sector; for the Chemicals sector – the MoM electricity consumption of the Chemicals sector and the forward energy price change.

In short, it is possible to conclude that that the month-over-month change in Swedish industrial electricity consumption accompanied by the CO2 intensity or occasionally by the forward energy price change, explains Swedish industrial sectors' stock returns.

A comparative graph of the t-statistic of MoM Electricity Consumption variable obtained by regressing the models for Italy and Sweden is presented in the figure below:

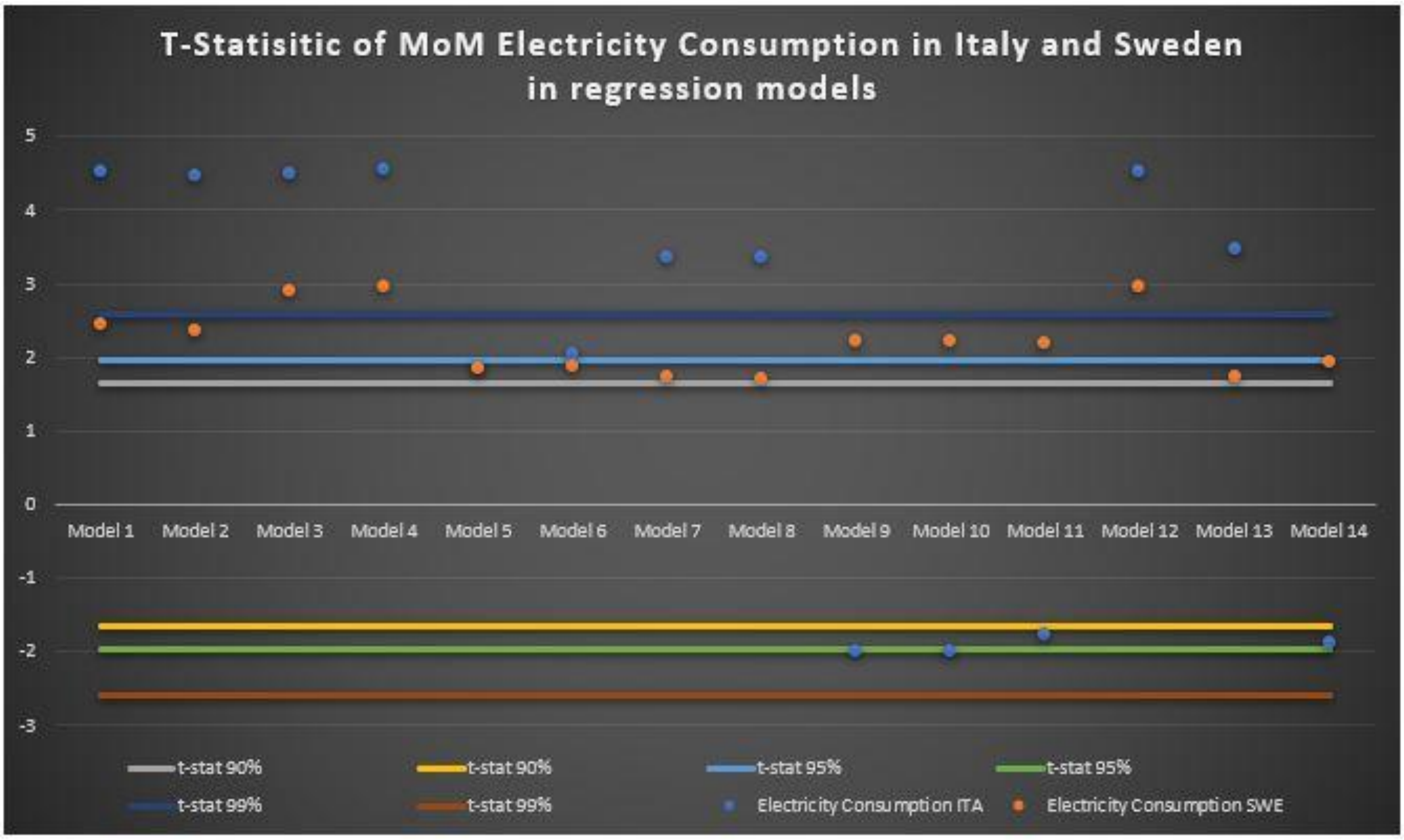


FIGURE 26 T-Statistic of MoM Electricity Consumption in Italy and Sweden in regression models. Represents the t-statistic of the electricity consumption variable, month-over-month data, obtained by regressing 14 models

on Italian and Swedish data. Lines relative to the confidence intervals (90%, 95% and 99%). Dots relative to the values of Italian and Swedish electricity consumption.

3.2.2. Year-over-year data

Like for the MoM data, the analysis on the year-over-year data is divided in two steps: first, the regressions with only energy efficiency measures are tested and one, if any, energy efficiency measure chosen to be used in further tests. Once again, the contemporaneous use of the energy efficiency measures is impossible due to the high correlation between them. After that the forward energy price change variable is added to the regression and the second test is performed.

Table 75: OLS Regressions: YoY Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against the YoY Electricity of Steel, Cement and Chemicals sectors and energy efficiency measures.

$Y1_t$ is YoY Swedish Basic Resources Stock Return at time t,
$X_{YoYECS(t-1)}$ is YoY Electricity Consumption of Basic Resources sector at time (*t-1)*;
$x_{PMEnInt(t-1)}$ is the Energy intensity of Basic Metals sector (koe/EURO 2015) at time (*t-1)*;
$x_{UConsS(t-1)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-1)*;
$x_{CO2Steel(t-1)}$ is the Intensity of CO2 emissions of Steel sector (tCO2/t) at time (*t-1)*.

Model 1: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \varepsilon_t$

Model 2: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_2 x_{PMEnInt(t-1)} + \varepsilon_t$

Model 3: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_3 x_{UConsS(t-1)} + \varepsilon_t$

Model 4: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_4 x_{CO2Steel(t-1)} + \varepsilon_t$

$Y2_t$ is YoY Swedish Construction & Materials Stock Return at time t,
$x_{YoYECCem(t-1)}$ is YoY Electricity Consumption of Construction & Materials sector at time (*t-4)*;
$x_{NMNEnInt(t-1)}$ is the Energy intensity of Non-Metal Mineral sector (koe/EURO 2015) at time (*t-1)*;
$x_{UConsC(t-1)}$ is the Intensity of Electricity Consumption of Cement sector per ton of production (kWh/t) at time (*t-1)*;
$x_{CO2Cement(t-1)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-1)*.

Model 5: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-1)} + \varepsilon_t$

Model 6: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-1)} + \beta_2 x_{NMMEnInt(t-1)} + \varepsilon_t$

Model 7: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-)} + \beta_3 x_{UConsC(t-1)} + \varepsilon_t$

Model 8 : $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-1)} + \beta_4 x_{CO2Cement(t-1)} + \varepsilon_t$

$Y3_t$ is YoY Swedish Chemicals Stock Return at time *t*,
$x_{YoYECChem(t-1)}$ is YoY Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{ChemEnInt(t-1)}$ is the Energy intensity of Chemicals sector (koe/EURO 2015) at time (*t-1)*;
$x_{CO2Chem(t-1)}$ is the Intensity of CO2 emissions of Chemicals sector (kCO_2/EURO 2015) at time (*t-1)*.

Model 9: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \varepsilon_t$

Model 10: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_2 x_{ChemEnInt(t-1)} + \varepsilon_t$

Model 11: $Y_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_4 x_{CO2Chem(t-1)} + \varepsilon_t$

	Basic Resources Sweden				Construction & Materials Sweden				Chemicals Sweden		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Electricity Consumption	0.414**	0.416**	0.403**	0.379**	-0.0300	-0.347*	-0.210	-0.155	0.579	0.651	0.298
	(0.017)	(0.012)	(0.019)	(0.028)	(0.884)	(0.079)	(0.353)	(0.488)	(0.278)	(0.299)	(0.664)
Energy Intensity value added		0.804***				1.709***				-2.899	
		(0.000)				(0.000)				(0.378)	
Energy Intensity			0.759*				0.000652				
			(0.068)				(0.538)				
CO2 Intensity				0.245*				-0.179			4.189
				(0.069)				(0.662)			(0.135)
Constant	0.100***	-0.154**	-0.139	-0.138	0.156***	-0.182**	0.0706	0.187*	0.306***	0.451***	0.0399
	(0.000)	(0.027)	(0.261)	(0.263)	(0.000)	(0.020)	(0.566)	(0.052)	(0.000)	(0.008)	(0.840)
N	141	132	132	132	142	132	120	120	142	132	120
adj. R^2	0.033	0.117	0.054	0.054	-0.007	0.112	-0.008	-0.010	0.001	-0.002	0.005
F	5.839	9.714	4.720	4.717	0.0213	9.287	0.513	0.418	1.187	0.851	1.319
p	**0.017****	**0.000118*****	**0.0105****	**0.0105****	0.884	**0.000171*****	0.600	0.659	0.278	0.429	0.271
df r	139	129	129	129	140	129	117	117	140	129	117

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year Basic Resources stock return corrected for inflation, the year-over-year Construction & Materials stock return corrected for inflation, the year-over-year Chemicals stock return corrected for inflation; the year-over-year electricity consumption of Basic Resources sector lagged by one month, the year-over-year electricity consumption of Construction & Materials sector lagged by one month, the year-over-year electricity consumption of Chemicals sector lagged by one month, and the energy efficiency measures: the value-added energy intensity of Primary Metals sector lagged by one month, the physical energy intensity of Steel sector lagged by one month, the physical CO2 emissions intensity of Steel sector lagged by one month, the value-added energy intensity of Non-metal Minerals sector lagged by one month, the physical electricity intensity of Cement sector lagged by one month, the physical CO2 emissions intensity of Cement sector lagged by one month, the value-added energy intensity of Chemicals sector lagged by one month, the value-added CO2 emissions intensity of Chemicals lagged by one month. Sample period: Jan 2010 – Dec 2019.

The table above shows a different situation with respect to the same table for the month-over-month data: while the electricity consumption variable is always statistically significant in explaining the Swedish Basic Resource stock returns with the positive sign (as expected), the electricity consumption of Construction & Materials sector is only weakly significant and only if combined with the value-added energy intensity. Besides, the sign (negative) of EC is reversed with respect to the theoretical setting. The electricity consumption of the Chemicals sector is never significant. However, all the significant energy efficiency measures have positive coefficients – consistent with the theoretical setting and meaning that the energy efficiency for those industrial sectors increases. The reason for that can be found in the logic of market valuation: the stock price increases if the productivity of a sector increases combined with the increase in the energy efficiency. An increase in the productivity is not accompanied by the investment in more efficient equipment and more sustainable production process - this indicates that the perspectives for the future growth are not good. If the sector has reached a certain level of energy efficiency and remains stable at it for a certain period (all Swedish industrial sectors made little progress from the point of view of energy efficiency in the period 2009-2020), the market values this sector as stagnant with low growth potential. The energy efficiency does not increase sufficiently (the energy/CO2 intensities do not decrease sufficiently), hence, the market values it negatively. So, the chain of impacts is the following: the increase in electricity consumption (decrease in YoY change) is not accompanied by the sufficient increase in energy efficiency because the production does not grow sufficiently fast, thus, even if the productivity grows a little, the market forms negative impression with respect to the perspectives of future product and reduces the stock price. That is why the electricity consumption of the Construction & Materials sector has a negative regression coefficient and the value-added energy efficiency has a positive sign. This is the same result as for the YoY data of Italian Construction & Materials sector. This is not surprising given that the two sectors are similar in a variety of aspects already mentioned at the beginning of this chapter. Also, both sectors are not highly performing from the point of view of energy efficiency showing only a slight upward trend in its growth which is more visible at the month-over-month level. At the year-over-year level the increase in energy input is not even enough to maintain the production at the same level as before. The energy efficiency is getting reduced gradually (energy intensity increases together with the energy input). So, the market reacts negatively to this dynamic.

The only energy efficiency measure which improves the performance of the model in which it is included, is the value-added energy intensity of the Non-Metallic Minerals sector added to model 6. It makes the model highly significant and the adjusted R2 positive (11,2%), hence, it will be retained in the model. The intensities of the Chemicals sector are not significant in the regressions. Only the value-added CO2 intensity of the Chemicals sector is significant at 15% level and has a positive sign, but it does not improve the adjusted R2 of the model. Therefore, the energy efficiency measures of the Chemicals sector are not considered for further analysis.

The electricity consumption variable of the Basic Resources and Chemicals sector presents the expected positive sign, being statistically significant only for the Basic Resources sector. The fact that the electricity consumption of the Chemicals sector is not significant could again be explained by the fact that many industrial sectors in Sweden are highly energy efficient (the most prominent improvement of energy efficiency occurred before 2009; Chemicals is very virtuous from the point of view of the level of energy efficiency) but have no strong incentive to continue the improvement of energy efficiency. Chemicals' electricity consumption and its energy efficiency (see for example Figure 25) move very little at yearly level in the long run (fast important oscillations are still present at monthly level). Hence, the trend is valued by the market as stagnant and difficult to interpret.

What follows is the regression analysis of the sector stock returns (Basic Resources, Construction & Materials, Chemicals) vs the relative year-over-year electricity consumption with the chosen energy efficiency measures, if any, and the forward energy price change.

Table 76: OLS Regressions: YoY Stock Returns of Basic Resources, Construction & Materials and Chemicals sectors against their YoY Electricity Consumption variables with chosen energy efficiency measures, YoY forward energy price change.

$Y1_t$ is YoY Swedish Basic Resources Stock Return at time *t*,
$x_{YoYECS(t-1)}$ is YoY Electricity Consumption of Basic Resources sector at time (*t-1)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at time (*t-1);*

Model 12: $Y_t = \beta_0 + \beta_1 x_{YoYECS(t-1)} + \beta_3 x_{YoYEP(t-1)} + \varepsilon_t$

$Y2_t$ is YoY Swedish Construction & Materials Stock Return at time *t*,
$x_{YoYECCem(t-1)}$ is YoY Electricity Consumption of Construction & Materials sector at time (*t-1)*;
$x_{CO2Cement(t-1)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-1)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at time (*t-1).*

Model 13: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem(t-1)} + \beta_2 x_{CO2Cement(t-1)} + \beta_3 x_{YoYEP(t-1)} + \varepsilon_t$

$Y3_t$ is YoY Chemicals Stock Return at time *t*,
$x_{YoYECChem(t-1)}$ is YoY Electricity Consumption of Chemical sector at time (*t-1)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at time (*t-1).*

Model 14: $Y3_t = \beta_0 + \beta_1 x_{YoYECChem(t-1)} + \beta_3 x_{YoYEP(t-1)} + \varepsilon_t$

	(12) Basic Resources Sweden	(13) Construction & Materials Sweden	(14) Chemicals Sweden
Electricity Consumption	0.426**	-0.382*	0.241
	(0.016)	(0.052)	(0.669)
Energy Intensity value added	0.809***	1.590***	
	(0.001)	(0.000)	
Fwd Energy Price	-0.0233	0.204**	0.307*
	(0.870)	(0.046)	(0.080)
Constant	-0.158**	-0.149*	0.310***
	(0.030)	(0.060)	(0.000)
N	132	132	142
adj. R^2	0.111	0.133	0.016
F	6.436	7.685	2.161
p	**0.000429*** **	**0.0000921*** **	0.119
df_r	128	128	139

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year stock return of the Basic Resources sector corrected for inflation, the year-over-year stock return of the Construction & Materials sector corrected for inflation, the year-over-year stock return of the Chemicals sector correct for inflation, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the year-over-year change of the electricity consumption of the Cement sector lagged by one month, the year-over-year change of the electricity consumption of the Chemical sector lagged by one month, the CO_2 intensity of the Cement sector lagged by one month, the year-over-year forward energy price change lagged by one month. The Sample period: Jan 2010 – Dec 2019.

The table above shows that the forward energy price change contributes to the improvement of the predictor power of Construction & Materials and Chemicals sectors. Besides, the sign of the coefficient is positive which means that the increase in the forward energy price does not boost the energy efficiency of this industrial sector under consideration which remains stagnant but directly boosts the sector productivity through the forced increase of energy input. The producers decide to produce more today rather than tomorrow after learning the news about the future increase in energy prices. The Basic Resources sector does not react to the changes in forward energy price because it may mitigate its impact by upscaling the production or by transferring the costs further to the intermediate or final consumers. Basic Resources sector is very energy-intensive by the value-added of its production increases more than proportionally with respect to the used electricity. So, it may mitigate the rise in the future price of electricity quite successfully.

In conclusion, it is necessary to say that the tests on Swedish data produced similar results with respect to the Italian data. The main result remains the same: the electricity consumption variable and energy efficiency measures are significant in explanation of stock returns. If used in a single-factor regression, the YoY sector electric energy variable is always significant in explaining the variation in Swedish sector stock prices (except for the Swedish Chemicals sector). This result is the same as for the tests on the MoM data, where also the electricity consumption of the Chemicals sector was statistically significant. If the electricity consumption is further adjusted by energy efficiency measures and/or the forward energy price change the inference results improve. The coefficient of determination increases visibly. The least energy efficient sector out of the three under consideration, the Construction & Materials sector, reacts to the changes in the forward energy price only at the year-over-year level when the value-added energy intensity is statistically significant. As it was mentioned before, at the YoY level the earnings and revenues become more important. Then, if the Construction & Materials sector is forced to use more electric energy to produce the same amount of input, it becomes particularly sensitive to the changes in energy prices, present and future. The energy efficiency level being difficult to raise in short time, the producers prefer to make structural changes to their productive facilities and/or upscale the production to mitigate the upcoming energy price increase. Therefore, they use more electric energy and produce more. Hence, the positive sign of the forward energy price change variable.

A comparative graph, analogous to that of the month-over-month data, of the t-statistic of YoY Electricity Consumption variable obtained by regressing the models for Italy and Sweden is presented in the figure below:

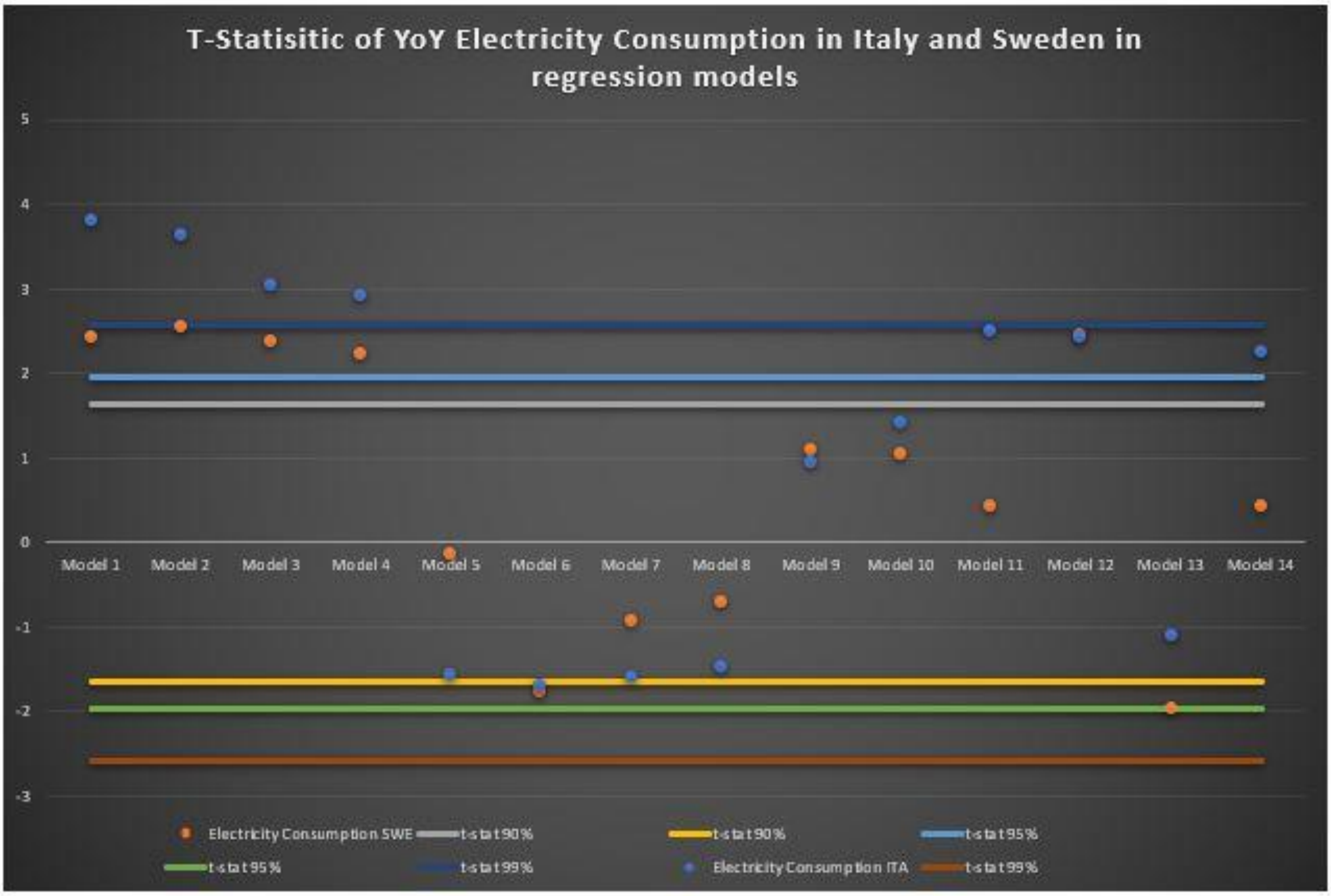


FIGURE 27 T-Statistic of YoY Electricity Consumption in Italy and Sweden in regression models. Represents the t-statistic of the electricity consumption variable, year-over-year data, obtained by regressing 14 models on Italian and Swedish data. Lines relative to the confidence intervals (90%, 95% and 99%). Dots relative to the values of Italian and Swedish electricity consumption.

Then, it is possible to confirm once again that in a study of the impact of electricity consumption on stock returns the knowledge of the energy efficiency of an energy-intensive industrial sector, combined with the availability of energy efficiency measures and the forward energy price series, is essential.

Table 77: Synthetic representation of the judgment on final regression results on MoM and YoY data of Swedish Basic Resources, Construction & Materials and Chemicals sectors stock returns, their sector electricity consumption, energy efficiency measures, forward energy price.

	Basic Resources MoM	Basic Resources YoY	Construction & Materials MoM	Construction & Materials YoY	Chemicals MoM	Chemicals YoY
Electricity Consumption	✓	✓	✓	✓	✓	✓
Energy Intensity value added	x	✓	x	✓	x	x
Energy Intensity	x	x	x	x	x	x
CO2 Intensity	✓	x	✓	x	x	x
Fwd Energy Price	x	x	x	✓	✓	✓
Adj R2	**7,2%**	**11,7%**	3,6%	13,3%	**5,4%**	**1,6%**

The table describes the results of the OLS regressions performed on the following variables: the month-over-month and the year-over-year stock returns of the Swedish Basic Resources sector corrected for inflation, the month-over-month and the year-over-year stock return of the Swedish Construction & Materials sector corrected for inflation, the month-over-month and the year-over-year stock return of the Swedish Chemicals sector corrected for inflation, the month-over-month change of the electricity consumption of the Basic Resources sector lagged by three months, the month-over-month change of the electricity consumption of the Construction & Materials sector lagged by four months, the month-over-month change of the electricity consumption of the Chemicals sector lagged by six months, the year-over-year change of the electricity consumption of the Basic Resources sector lagged by one month, the year-over-year change of the electricity consumption of the Construction & Materials sector lagged by one month, the physical CO2 intensity of the Basic Resources sector lagged by three months, the physical CO2 intensity of the Cement sector lagged by one and four months, the month-over-month forward energy price change lagged by six months, the year-over-year forward energy price change lagged by one month. The Sample period for MoM: Feb 2009 – Dec 2019, for YoY: Jan 2010 – Dec 2019.

The table above shows that the Swedish market pays most attention to the electricity consumption variable, the value-added energy intensity, and the CO2 intensity in evaluating the industrial stock returns. If the energy efficiency measures do not convey clear information, the market relies on the forward energy price change. The physical energy intensity is the measure which is the least important for the market in making decisions on the growth potential of this or that industrial sector.

If the results of the above table are compared to those of the analogous Table 53 for the Italian data, it is evident that the Italian energy-intensive sectors, which at the beginning of the sample period are at a lower energy efficiency level with respect to Sweden, are forced by the European climate policies and the competitors to improve the relative energy efficiency rapidly in a pronounced way. The market notices these improvements by considering the values of the energy intensities. The only

Italian sector whose energy efficiency is high is the Chemical sector. Therefore, the electricity consumption of this sector already incorporates the information which could be added by the energy intensities. So, the market values the sector CO_2 intensity and the reaction to the change in forward energy price and the change in carbon prices instead. This is similar to what happens in Sweden.

All the results described above are consistent with the energy efficiency situation of the industrial sectors in Sweden and in Italy. Hence, the regression results should be considered reliable.

Conclusion.

On the basis of the concept of entropy in the production process - not all the energy is used to produce the useful output but a part of it gets wasted and even pollutes the environment - the present research elaborated a two-period version of a dual-output model (with desired, neoclassical output, and undesired, CO_2 emissions, output) of the production process in order to derive a simple expression for a stock return. Using the derived theoretical model, the thesis tests empirically the impact of the industrial electricity consumption growth on the sector stock returns of three energy-intensive industrial sectors (Basic Resources, Construction & Materials, Chemicals) based on Italian and Swedish data. The model is in simplified form, not considering labour and capital, for the feasibility of econometric analysis. By following the idea by Burnside et al. (1995) [BER 95] that the "line speed", the intensity of the use of machinery in production process, should enter the production function, also here similar variables expressed as energy and CO_2 emissions intensities are added to the model. These variables are commonly considered as energy efficiency measures which may vary throughout the sample period. The model by BER 95 was then modified to account for time-varying coefficients and the side-production of CO_2 emissions resulting from the use of energy input.

The results of this research on industrial electricity consumption growth rates referred to Italian and Swedish energy-intensive industrial sectors and their role in asset pricing are encouraging. All the used variables are significant in explaining industrial stock returns. They confirm the results obtained by one of the reference articles of this research, Da Zhi et al (2017), for the US data: the industrial electricity consumption variable (its year-over-year change) does influence the industrial stock returns and does so with significant predictive power. Besides, the tests on the month-over-month data confirm the general tendency introduced by Da Zhi.

The results of the research are analysed from the perspective of interactions between the electricity consumption and energy efficiency (product or value-added per unit of energy used, i.e. a definition of productivity). Following a production-based theory, productivity is then considered by the stock market for the setting of the sector stock price and the decision on the size of the risk premium to apply to the stock returns.

The investigation of the way by which the electricity consumption influences the stock returns gave the expected result: it happens through the impact on the productivity which then influences the financial values such as the book-to-market ratio and the price-earnings ratio. The relative tests on the Italian data showed that these ratios are explained by the sector electricity consumption together with the energy efficiency variables and occasionally by the changes in forward energy and carbon price. This result is true for the Italian Basic Resources and the Italian Chemicals sectors. The Italian

Construction & Materials sector, being the least energy efficient sector under consideration, needs the financial ratios for the explanation of the relative stock returns as the stock market of the sector apparently does not appreciate the information content of energy input data. The electricity consumption variable itself proved to be significant in the explanation of both Italian and Swedish stock returns in both month-over-month and year-over-year tests. The sign of the regression coefficient was generally as expected with some rare exceptions: the Italian Chemicals sector, which presents a very high growth in energy efficiency, and the Italian and Swedish Construction & Materials sectors, which in turn are the least energy efficient sectors under consideration. The first case is the best proof of the principle of energy efficiency: the industrial sector manages to produce bigger quantity of product using smaller amount of energy input. The second case is the opposite – lagging behind the pace of the energy efficiency: the industrial sector uses bigger amount of energy input to produce even smaller amount of product than before.

The energy and CO2 intensities, which are closely related to each other, interact with the general energy efficiency of the industrial sector and generally behave as expected in explaining the sector stock return. The empirical analysis shows an exception when the industrial sector improves the energy efficiency very rapidly. In this case the energy efficiency measures present some unexpected regression signs but be still statistically significant in explaining the sector stock returns. It can also happen that the industrial sector (Chemicals sector in Italy) improves its energy efficiency at such a high speed that the electricity consumption variable already includes all the information on the energy efficiency and no energy or CO2 intensities are needed for the explanation of industrial stock returns. Another special case is when the industrial sector is not virtuous from the point of view of energy efficiency (Construction & Materials sectors in Sweden). The energy efficiency measures feature unexpected signs but are statistically significant in the regressions. In this case the energy and CO2 intensities exercise their correcting effect: the increase in electricity usage is not translated proportionally to the increase in productivity but is reduced due to the low energy efficiency of the industrial sector.

The sign of the regression coefficients of the energy efficiency measures remains the same for each Italian industrial sector no matter whether the month-over-month or the year-over-year data is used (apart from the Italian Chemicals sector which is abnormally energy efficient with respect to other two Italian industrial sectors). This means that the correcting impact of these intensities is stable and strong. The same result is true for the Swedish data: MoM and YoY tests feature the same sign of the coefficients of the energy efficiency measures. It is reversed with respect to Italy due to a different energy efficiency situation of Swedish industrial sectors (generally higher than in Italy) combined with the low speed of improvement of Swedish sector energy efficiency after 2009.

Based on the empirical tests, the model also includes the forward energy price change as an explanatory variable. The carbon price change, which was added to the Italian regression models without it being part of the solution to the energy-centred production problem, was aimed at checking the reliability of the theoretical setting applied to the Italian industrial sectors. Theoretically the carbon price, as well as the forward energy price, negatively impacts the productivity of the sector and, hence, urges the improvement of energy efficiency to mitigate this impact. It is important to remember that being more energy efficient is favourable both from the point of view of productivity, which is getting increased, and from the point of view of the reduction of CO_2 emissions. This theory was checked with some unexpected results. While the forward energy price change behaved mainly as expected, being the booster of energy efficiency (in Italy), the carbon price change was counterbalanced by the upscaled production without leading to the improvement of energy efficiency. For the Swedish data the same effect was observed for the forward energy price change. This concerns mainly the impact of the carbon price change on the stock returns of the Italian Construction & Materials (the least energy efficient out of three sectors) and the Italian Chemicals sectors (the top energy efficient sector out of three) and the impact of the forward energy price change on the Swedish Chemicals sector (the only industrial sector in Sweden which increased its energy consumption in the period 2000 – 2018) and the Swedish Construction & Materials sector.

The Italian dataset used in this research gave some important results. All the used variables were statistically significant in explaining industrial stock returns. However, the dataset is not large enough to confirm the theoretical mechanism which links the variables to stock returns. To enrich the dataset and to be able to draw the conclusions the Swedish electricity data were used in the last part of the research. The results confirmed all the tendencies that were discovered on the basis of the Italian data and added some new insights relative to the country-specific sector energy efficiency situation.

The data relative to other European countries would enlarge the dataset and add robustness to the results. Besides, a deeper analysis of the physics of the production process considering labour and capital and the multi-staged dynamics would be desirable. All these matters are left for future research.

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APPENDIX A

1. What follows here is the comparison on the trends of the sector electricity consumption and the industrial production index in Italy. The sectors under consideration are the energy intensive ones which are the object of the analysis of the present thesis (Steel, Non-ferrous Metals, Cement and Chemicals). The reference point is the relative average value either of 2010 or of 2015 which is taken as 100.

   1) **Base year 2010** (2010=100)

   a) Steel sector

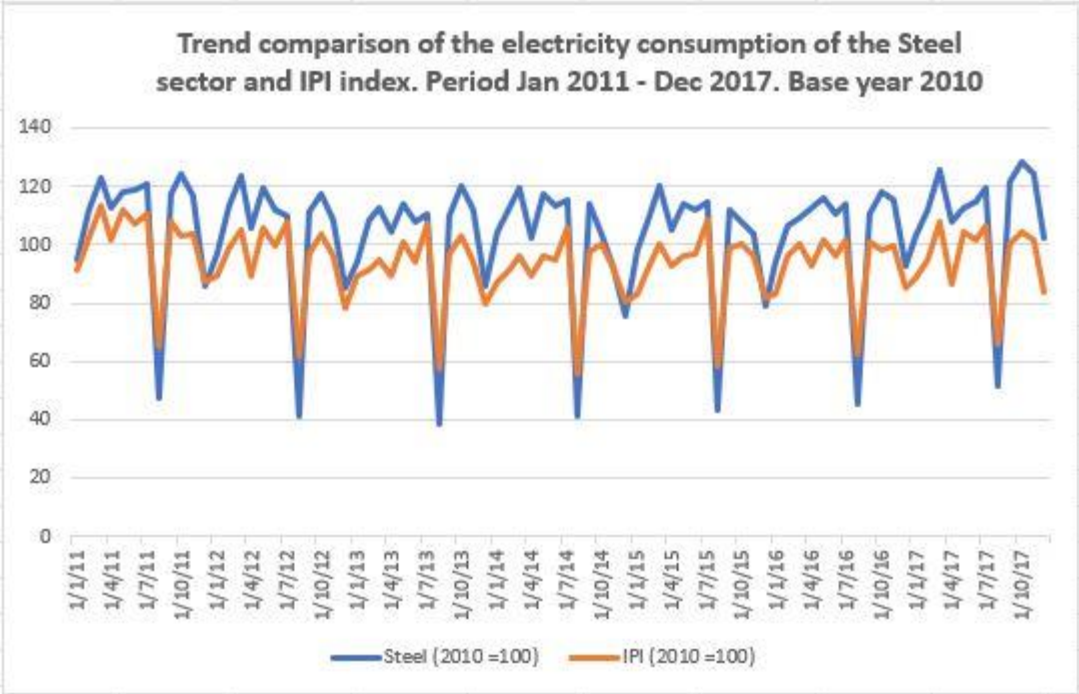


FIGURE 8 The trend comparison of the monthly Steel sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2010=100). The orange line refers to the IPI index, the blue line refers to the Steel sector electricity consumption. Sample period January 2011 – December 2017. Monthly data.

Correlation between the series is 0,93. The series overlap almost perfectly if not for the magnitude.

b) Non-ferrous Metals sector

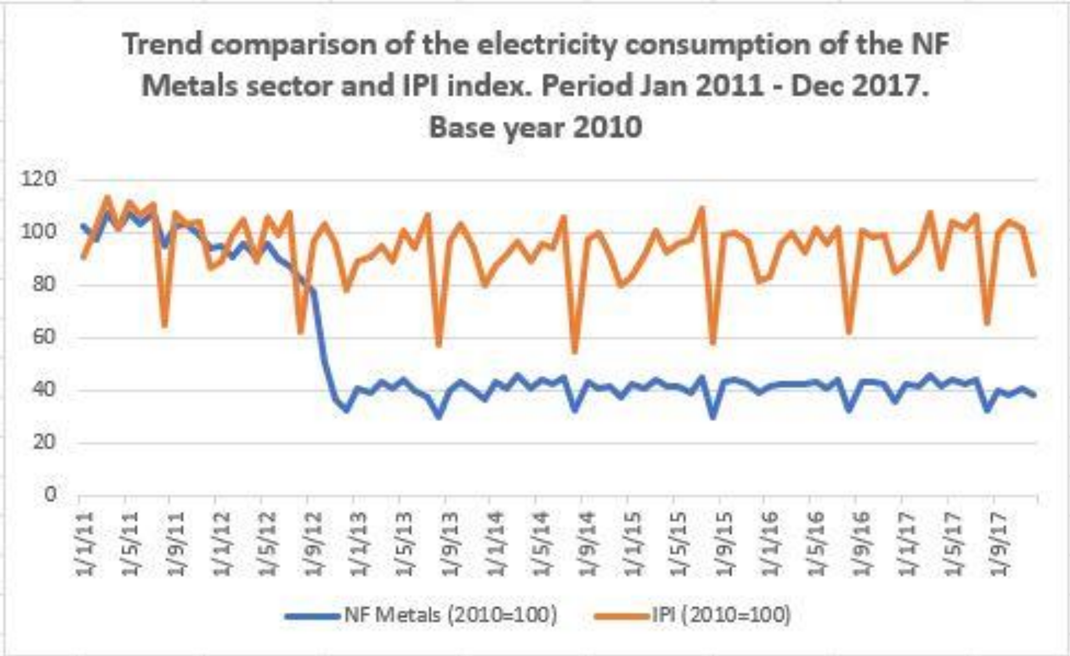


FIGURE 9 The trend comparison of the monthly Non-ferrous Metals sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2010=100). The orange line refers to the IPI index, the blue line refers to the Non-ferrous Metals sector electricity consumption. Sample period January 2011 – December 2017. Monthly data.

Correlation between the series is 0,32. Starting from the year 2012 the series do not overlap anymore any show weak correlation.

c) Cement sector

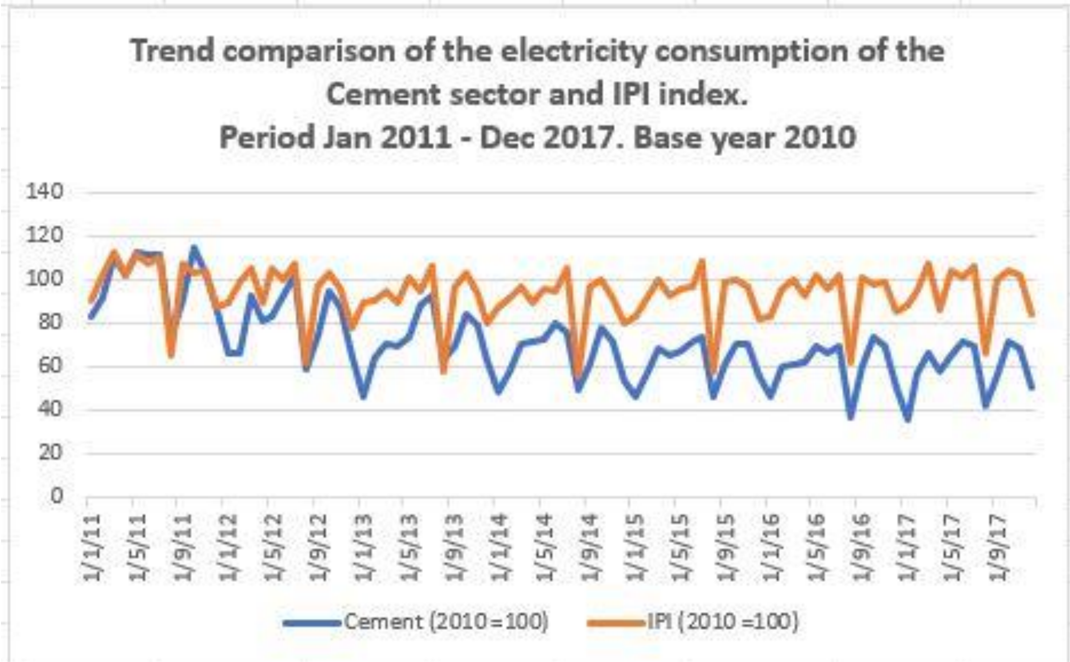


FIGURE 10 The trend comparison of the monthly Cement sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2010=100). The orange line refers to the IPI index, the blue line refers to the Cement sector electricity consumption. Sample period January 2011 – December 2017. Monthly data.

Correlation between the series is 0,62 which means that the series do not overlap but follow the same trend over the whole sample period. The correlation value is significant in this case.

d) Chemicals sector

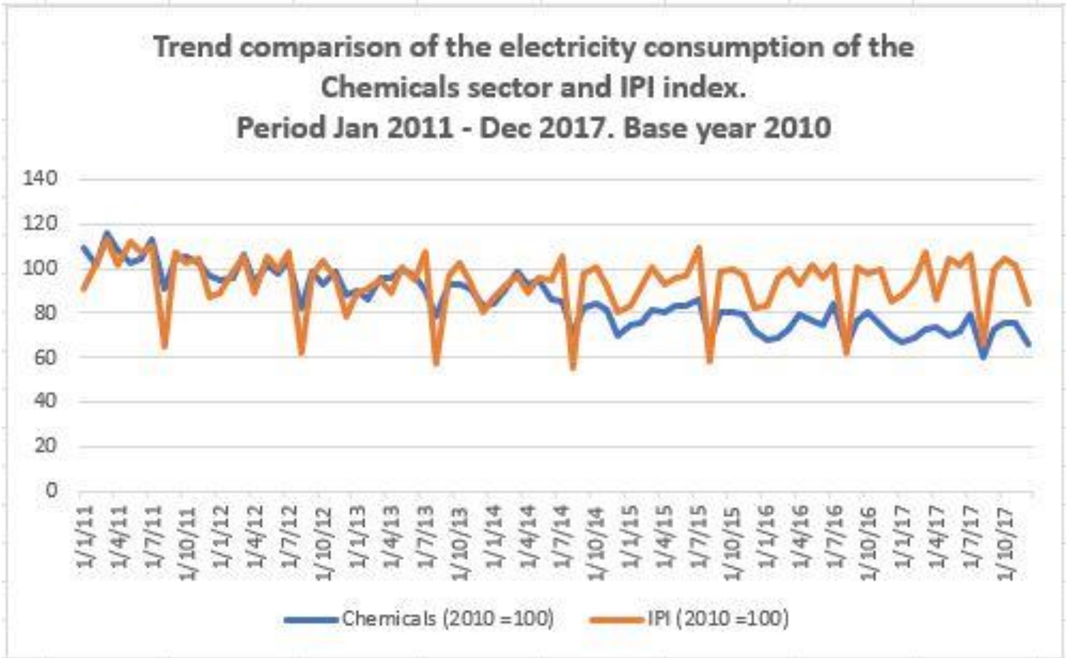


FIGURE 11 The trend comparison of the monthly Chemicals sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2010=100). The orange line refers to the IPI index, the blue line refers to the Chemicals sector electricity consumption. Sample period January 2011 – December 2017. Monthly data.

Correlation between the series is 0,46. This value is borderline.

The visual overlapping graphs and the correlation values show that if year 2010 is considered as the base year, then it is mostly the Steel sector electricity consumption that tracks the industrial production index in Italy for the period between 2011 and 2018. However, the results for the Cement sector and the Chemicals sector deserve attention because the correlation is visible.

2) **<u>Base year 2015</u>** (2015=100)

e) Steel sector

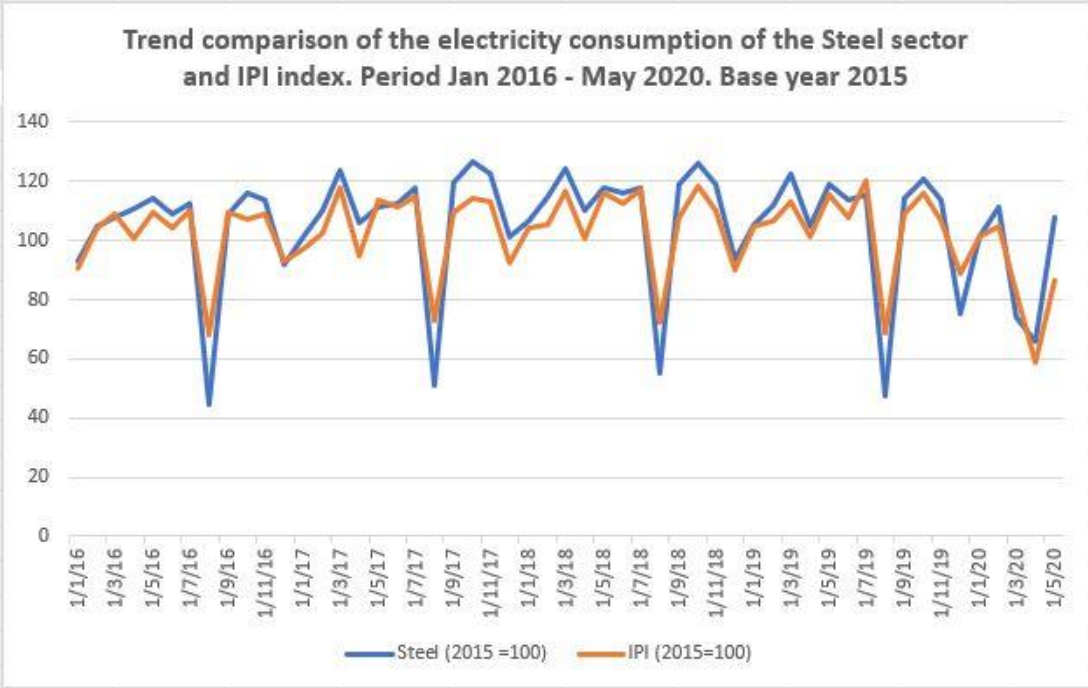


FIGURE 12 The trend comparison of the monthly Steel sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2015=100). The orange line refers to the IPI index, the blue line refers to the Steel sector electricity consumption. Sample period January 2016 – May 2020. Monthly data.

Correlation between the series is 0,93. As for the base year 2010, the series overlap almost perfectly.

f) Non-ferrous Metals sector

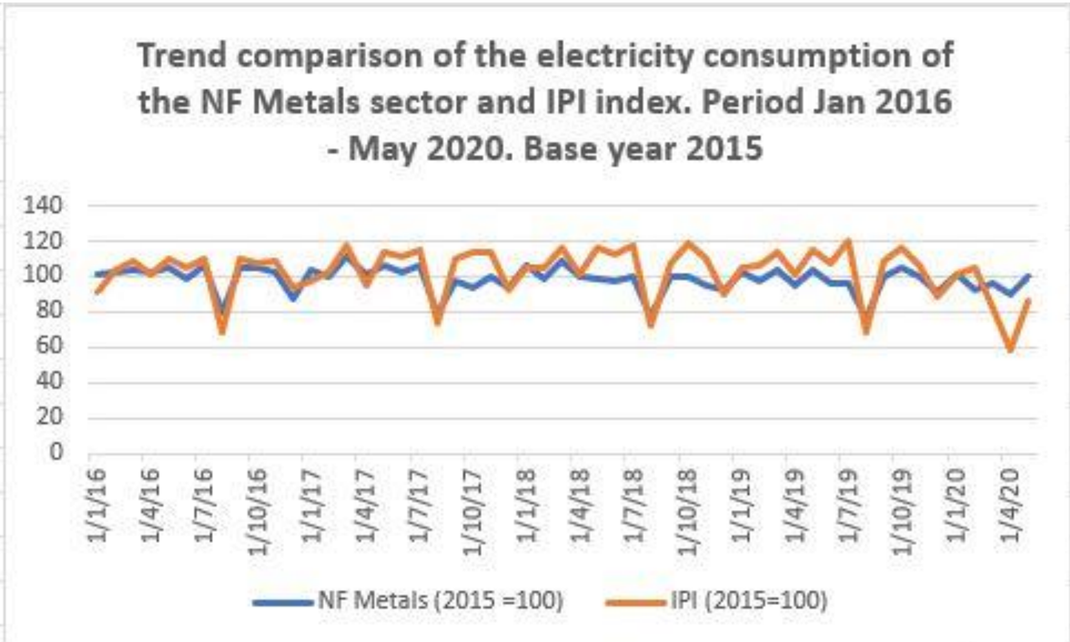


FIGURE 13 The trend comparison of the monthly Non-ferrous Metals sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2015=100). The orange line refers to the IPI index, the blue line refers to the Non-ferrous Metals sector electricity consumption. Sample period January 2016 – May 2020. Monthly data.

Correlation between the series is 0,76. This result is very different from the previous case with 2010 as the base year. The series are highly correlated.

g) Cement sector

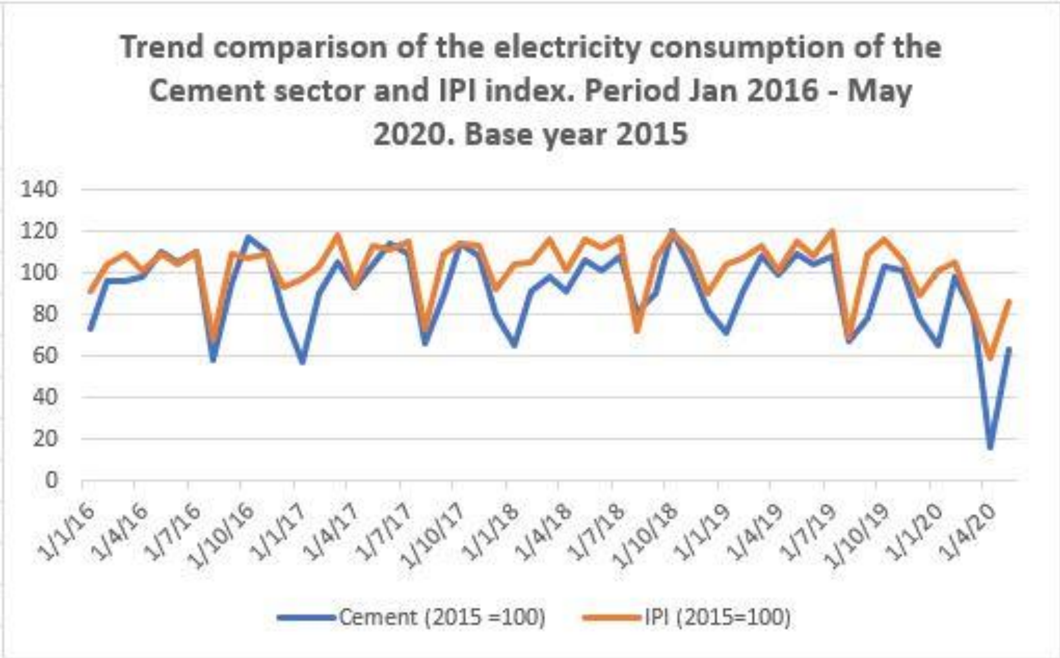


FIGURE 14 The trend comparison of the monthly Cement sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2015=100). The orange line refers to the IPI index, the blue line refers to the Cement sector electricity consumption. Sample period January 2016 – May 2020. Monthly data.

Correlation between the series is 0,81. This value is much higher than for the previous case with 2010 as the base year.

h) Chemicals sector

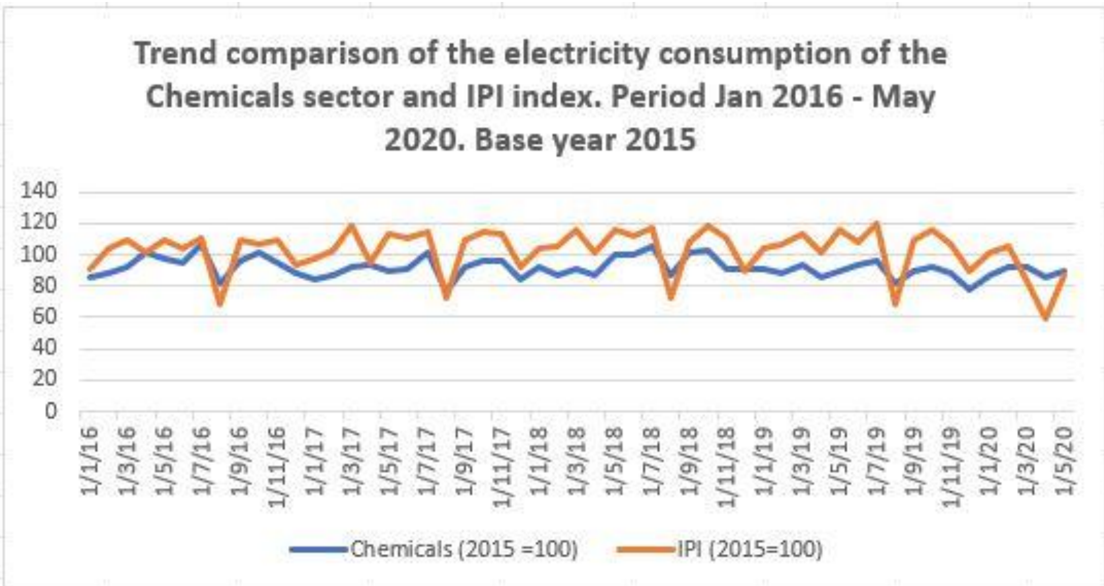


FIGURE 15 The trend comparison of the monthly Chemicals sector electricity consumption and IPI, the monthly Italian production index. Trend variation with respect to the average of the base year (2015=100). The orange line

refers to the IPI index, the blue line refers to the Chemicals sector electricity consumption. Sample period January 2016 – May 2020. Monthly data.

Correlation between the series is 0,64. Also for the Chemicals sector the correlation value has increased with respect to the previous case.

If the base year is 2015 and the period is 2016-2020, then the correlation between the series is significantly higher with respect to the period 2011-2017 base year 2010, and now it is not only the Steel sector electricity consumption which tracks the industrial production index, but the electricity consumption of all the four energy intensive sectors which are used in the analysis. The correlation values are always higher than 0,6.

Whatever year is taken as the base year, it is possible to state that the correlation between the industrial electricity consumption and the industrial production is clearly visible. Therefore, the electricity consumption variable is rightfully tested as the predictor of industrial sector stock returns considering its impact on the industrial production.

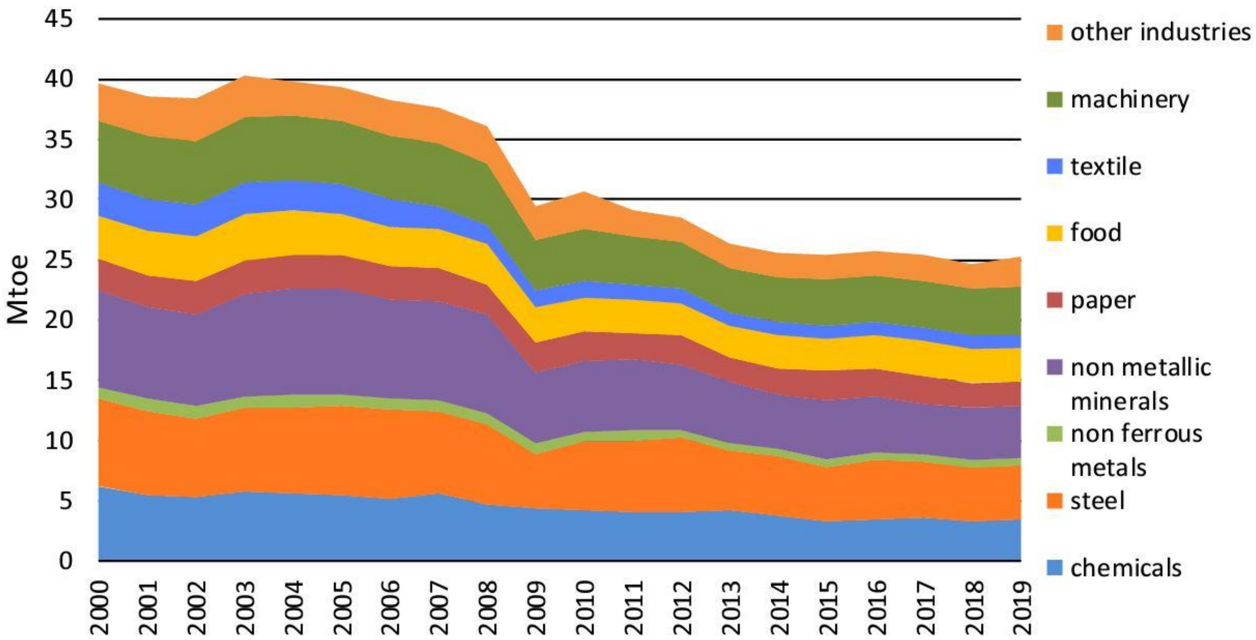


FIGURE 16 Energy Consumption of Italian industrial sectors (Mtoe). Yearly data. Sample period 2000 – 2019.

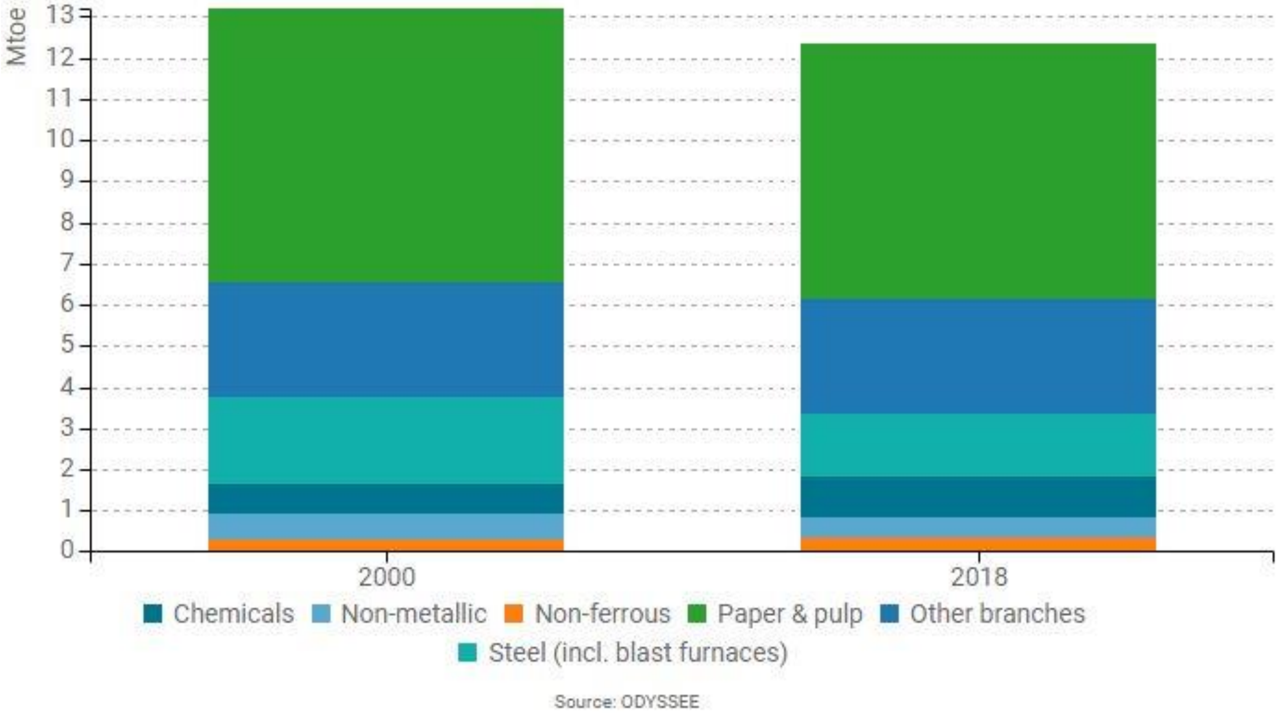
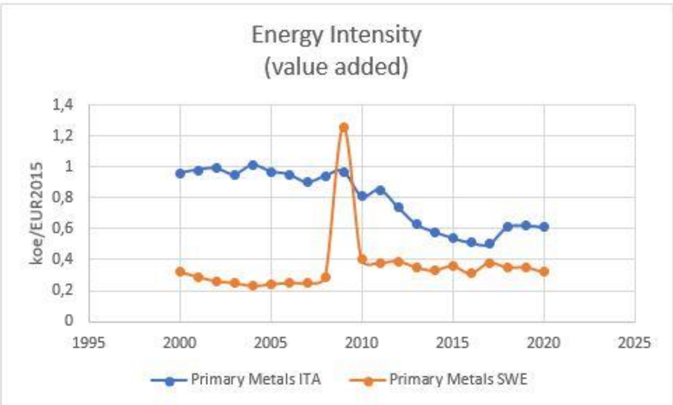


FIGURE 17 Energy Consumption of Swedish industrial sectors (Mtoe). Comparison 2000 - 2018.

2. **Graphical comparison of energy efficiency measures of Italy and Sweden** (lower values indicate higher energy efficiency)**:**



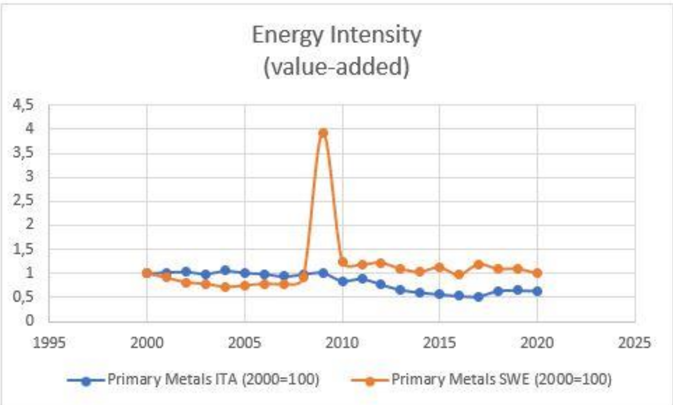


FIGURE 18 Energy Intensity, value-added; of Italian and Swedish Primary Metals industrial sectors. Indicate the quantity of used energy (koe) per 1€ of production value measured in Euro 2015. Yearly data. Sample period 2000 – 2020.

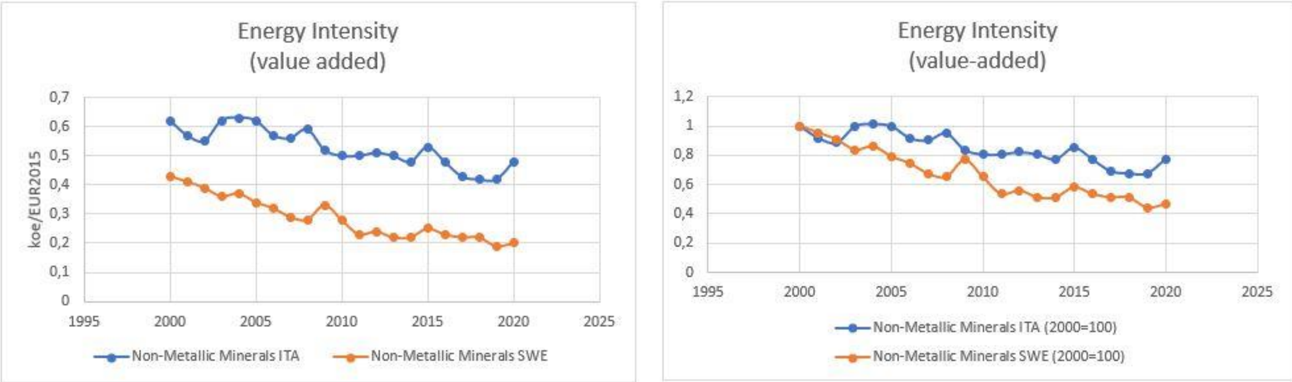


FIGURE 19 Energy Intensity, value-added; of Italian and Swedish Non-Metallic Minerals industrial sectors. Indicate the quantity of used energy (koe) per 1€ of production value measured in Euro 2015. Yearly data. Sample period 2000 – 2020.

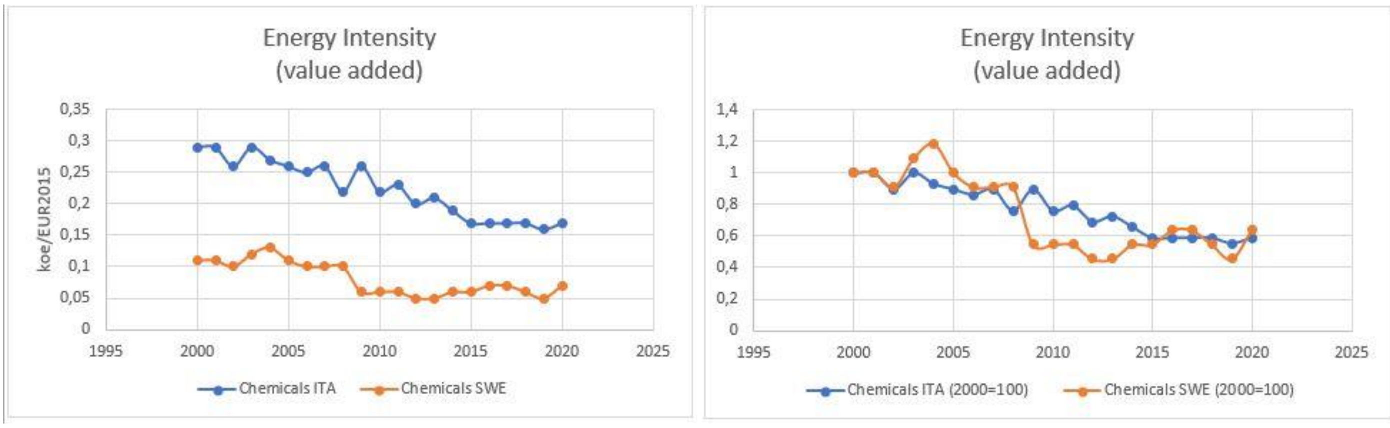


FIGURE 20 Energy Intensity, value-added; of Italian and Swedish Chemicals industrial sectors. Indicate the quantity of used energy (koe) per 1€ of production value measured in Euro 2015. Yearly data. Sample period 2000 – 2020.

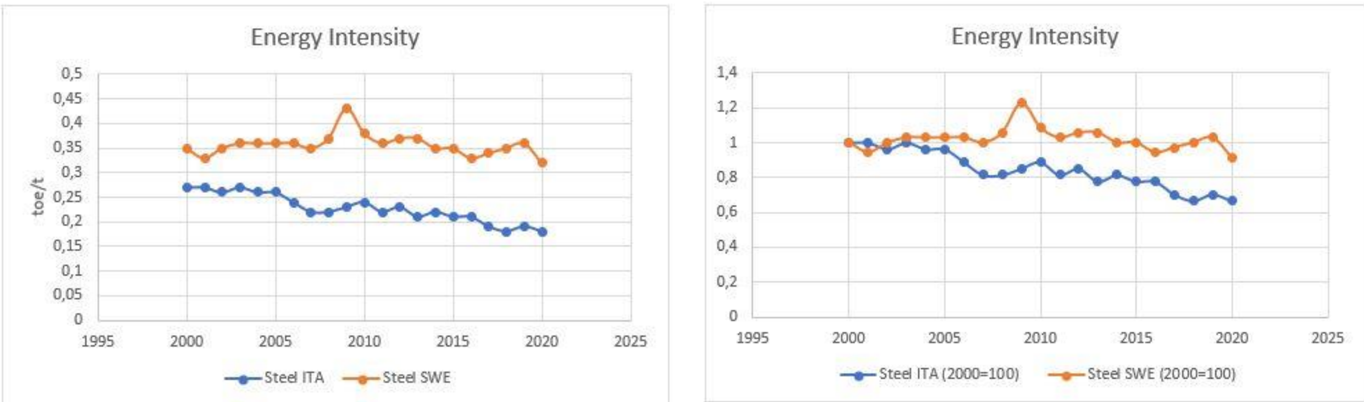
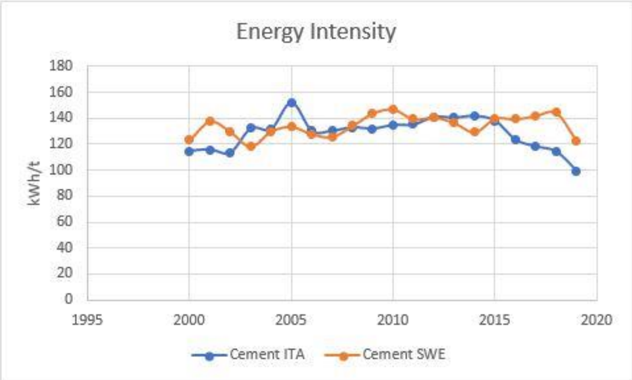


FIGURE 21 Energy Intensity, per ton of product, of Italian and Swedish Steel industrial sectors. Indicate the quantity of used energy (toe) per one ton of production. Yearly data. Sample period 2000 – 2020.



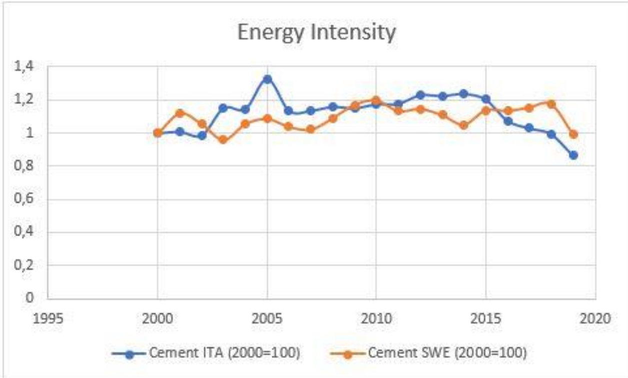
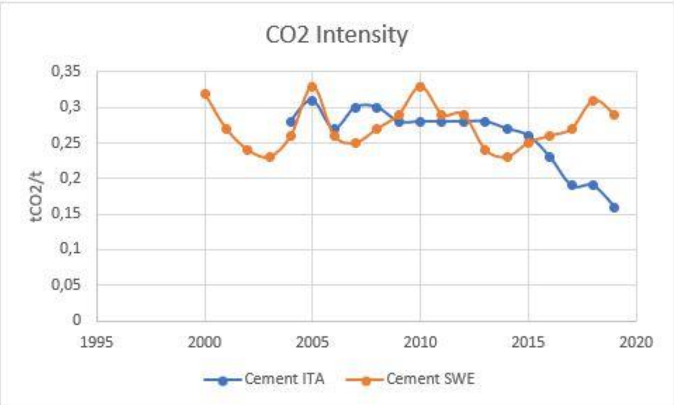


FIGURE 22 Energy Intensity, per ton of product, of Italian and Swedish Cement industrial sectors. Indicate the quantity of used energy (toe) per one ton of production. Yearly data. Sample period 2000 – 2020.



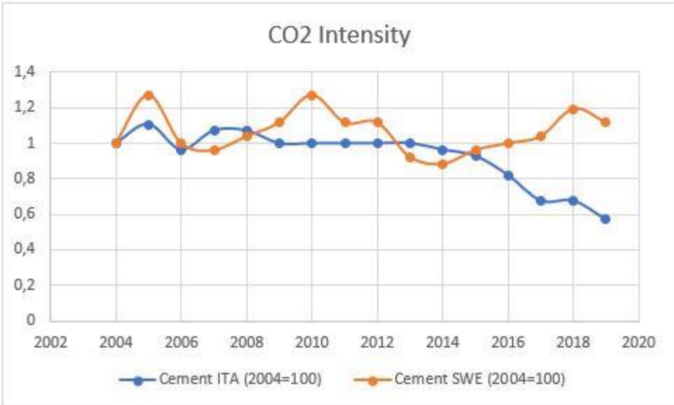
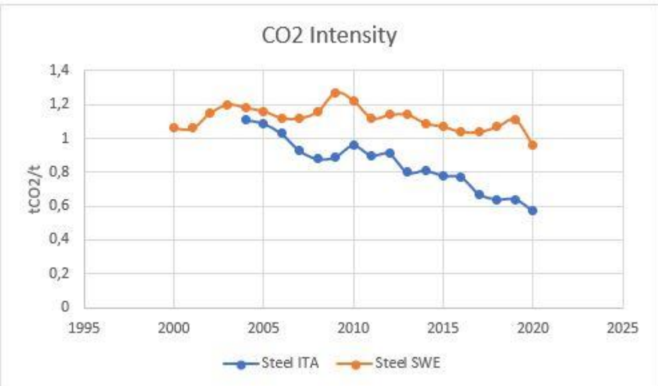


FIGURE 23 CO2 Intensity, per ton of product, of Italian and Swedish Cement industrial sectors. Indicate the quantity of CO2 emissions (tCO2) per one ton of production. Yearly data, base year 2009. Sample period 2000 – 2020.



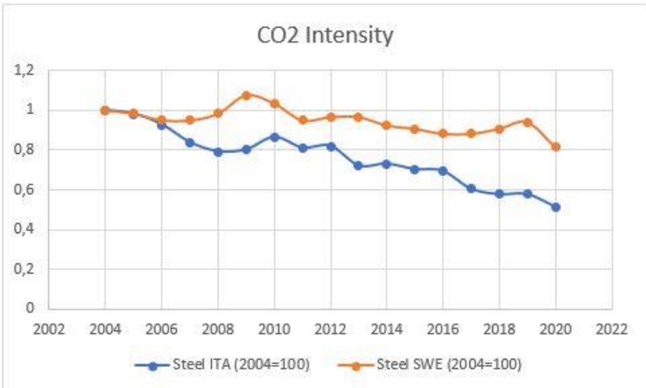


FIGURE 24 CO2 Intensity, per ton of product, of Italian and Swedish Steel industrial sectors. Indicate the quantity of CO2 emissions (tCO2) per one ton of production. Yearly data, base year 2009. Sample period 2000 – 2020.

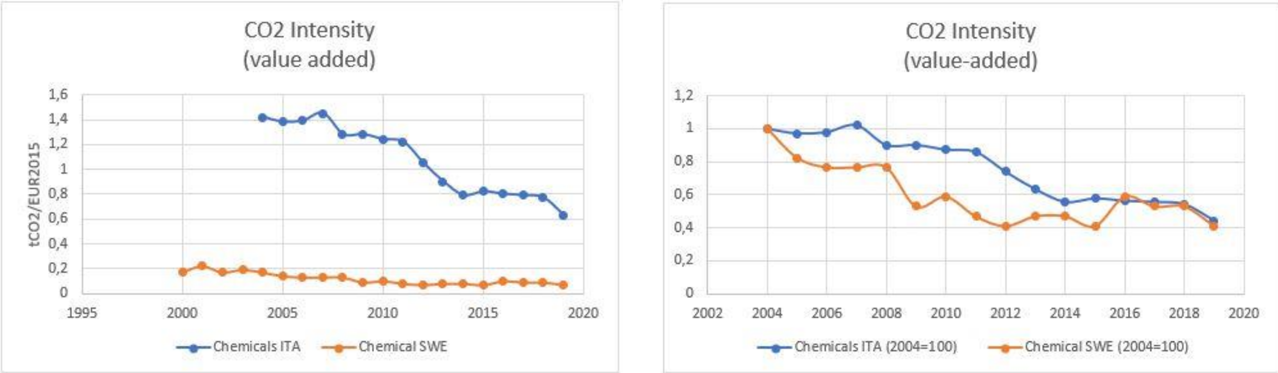


FIGURE 25 CO2 Intensity, value added, of Italian and Swedish Chemicals industrial sectors. Indicate the quantity of CO2 emissions (tCO2) per 1€ of production value measured in Euro 2015. Yearly data, base year 2009. Sample period 2000 – 2020.

APPENDIX B

Correlation matrices with all the variables used in the analysis of the three energy-intensive industrial sectors (Basic Resources, Construction & Materials, Chemicals):

ITALY:

Basic Resources:

Table 27: Correlation Matrix of MoM Basic Resources Return, MoM electricity consumption variables of Steel and Non-ferrous Metals sectors, the energy efficiency measures, MoM forward energy price change, MoM carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations MoM Basic Resources

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Stock Return	1.000									
(2) Electricity Consumption Steel	0.014	1.000								
(3) Electricity Consumption Nonferrous Metals	0.020	0.216	1.000							
(4) Energy Intensity value added	-0.017	0.008	-0.067	1.000						
(5) Energy Intensity	-0.052	0.092	-0.008	0.708	1.000					
(6) CO2 Intensity	-0.034	0.136	-0.047	0.826	0.963	1.000				
(7) Fwd Energy Price	-0.125	-0.009	-0.027	-0.099	-0.160	-0.151	1.000			
(8) CO2 price	0.127	0.009	0.122	-0.070	0.053	0.016	-0.089	1.000		
(9) Book-to-Market	-0.017	0.211	-0.140	0.562	0.394	0.550	-0.042	-0.065	1.000	
(10) Price-Earnings	-0.026	0.235	-0.035	0.294	0.265	0.331	-0.099	-0.080	0.740	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Basic Resources sector corrected for inflation, the month-over-month change of the electricity consumption of the Steel sector lagged by six months, the month-over-month change of the electricity consumption of the Non-ferrous Metals sector lagged by six months, the value-added energy intensity of the Primary Metals sector lagged by six months, the physical energy intensity of the Steel sector lagged by six months, the physical CO2 emissions intensity of the Steel sector lagged by six months, the month-over-month change in forward energy price lagged by five months, the month-over-month change in carbon permits' price lagged by five months, the book-to-market ratio of the Metals sector lagged by six months, the price-earnings ratio of the Metals sector lagged by six months.

Table 28: Correlation Matrix of YoY Basic Resources Return, YoY electricity consumption variables of Steel sector, the energy efficiency measures, YoY forward energy price change, YoY carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations YoY Basic Resources

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Stock Return	1.000								
(2) Electricity Consumption	0.147	1.000							
(3) Energy Intensity value added	0.007	0.071	1.000						
(4) Energy Intensity	0.182	-0.040	0.672	1.000					
(5) CO2 Intensity	0.126	-0.038	0.795	0.962	1.000				
(6) Fwd Energy Price	0.148	0.257	0.221	-0.092	-0.132	1.000			
(7) CO2 Price	0.302	0.466	-0.359	-0.218	-0.316	0.265	1.000		
(8) Book-to-Market	0.077	-0.096	0.567	0.383	0.555	-0.436	-0.366	1.000	
(9) Price-Earnings	0.157	-0.294	0.252	0.231	0.295	-0.406	-0.285	0.736	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Basic Resources sector corrected for inflation, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the value-added energy intensity of the Primary Metals sector lagged by one month, the physical energy intensity of the Steel sector lagged by one month, the physical CO2 emissions intensity of the Steel sector lagged by one month, the year-over-year forward energy price change lagged by one month, the year-over-year change in carbon permits' price lagged by one month, the book-to-market ratio of the Metals sector lagged by one month, the price-earnings ratio of the Metals sector lagged by one month.

Construction & Materials:

Table 29: Correlation Matrix of MoM Construction & Materials Return, MoM electricity consumption variables of Cement, the energy efficiency measures, MoM forward energy price change, MoM carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations MoM Construction & Materials

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Stock Return	1.000								
(2) Electricity Consumption	0.303	1.000							
(3) Energy Intensity value added	0.123	-0.070	1.000						
(4) Energy Intensity	0.123	-0.089	0.954	1.000					
(5) CO2 Intensity	0.112	-0.104	0.880	0.920	1.000				
(6) Fwd Energy Price	-0.113	0.156	0.013	0.003	-0.053	1.000			
(7) CO2 Price	0.144	0.117	-0.034	-0.062	-0.077	-0.042	1.000		
(8) Book-to-Market	0.041	-0.006	0.154	0.032	0.229	-0.023	0.140	1.000	
(9) Price-Earnings	-0.172	0.008	0.014	-0.023	0.074	0.025	-0.083	0.048	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Construction & Materials sector corrected for inflation, the month-over-month change of the electricity consumption of the Cement sector lagged by three months, the value-added energy intensity of the Non-Metallic Mineral sector lagged by three months, the physical electricity intensity of the Cement sector lagged by three months, the physical CO2 emissions intensity of the Cement sector lagged by three months, the month-over-month change in forward energy price lagged by four months, the month-over-month change in carbon permits' price lagged by one month, the book-to-market ratio of the Cement sector lagged by three months, the price-earnings ratio of the Cement sector lagged by three months.

Table 30: Correlation Matrix of YoY Construction & Materials Return, YoY electricity consumption variables of Cement, the energy efficiency measures, YoY forward energy price change, YoY carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations YoY Construction & Materials

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Stock Return	1.000								
(2) Electricity Consumption	-0.031	1.000							
(3) Energy Intensity value added	0.081	-0.199	1.000						
(4) Energy Intensity	0.102	-0.244	0.954	1.000					
(5) CO2 Intensity	0.107	-0.309	0.885	0.930	1.000				
(6) Fwd Energy Price	-0.430	0.205	-0.104	-0.147	-0.312	1.000			
(7) CO2 Price	0.134	0.206	-0.295	-0.302	-0.475	0.265	1.000		
(8) Book-to-Market	-0.221	-0.074	0.146	0.026	0.208	-0.262	-0.080	1.000	
(9) Price-Earnings	-0.294	0.405	-0.004	-0.037	0.025	0.249	0.015	0.015	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Construction & Materials sector corrected for inflation, the year-over-year change of the electricity consumption of the Cement sector lagged by one month, the value-added energy intensity of the Non-Metallic Mineral sector lagged by one month, the physical electricity intensity of the Cement sector lagged by one month, the physical CO2 emissions intensity of the Cement sector lagged by one month, the year-over-year change in forward energy price change lagged by one month, , the year-over-year change in carbon permits' price lagged by one month, the book-to-market ratio of the Cement sector lagged by one month, the price-earnings ratio of the Cement sector lagged by one month.

Chemicals:

Table 31: Correlation Matrix of MoM Chemicals Return, MoM electricity consumption variables of Chemicals, the energy efficiency measures, MoM forward energy price change, MoM carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations MoM Chemicals

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Stock Return	1.000							
(2) Electricity Consumption	-0.178	1.000						
(3) Energy Intensity value added	-0.000	-0.100	1.000					
(4) CO2 Intensity value added	-0.042	-0.026	0.885	1.000				
(5) Fwd Energy Price	-0.158	-0.180	-0.031	-0.012	1.000			
(6) CO2 Price	0.243	-0.162	-0.031	-0.038	-0.045	1.000		
(7) Book-to-Market	-0.089	-0.018	0.523	0.737	-0.094	-0.062	1.000	
(8) Price-Earnings	0.122	-0.064	-0.274	-0.327	-0.024	0.031	-0.143	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Chemical sector corrected for inflation, the month-over-month change of the electricity consumption of the Chemical sector lagged by one month, the value-added energy intensity of the Chemical sector lagged by one month, the value-added CO2 emissions intensity of the Chemical sector lagged by one month, the month-over-month change in forward energy price lagged by five months, the month-over-month change in carbon permits' price lagged by five months, the book-to-market ratio of the Chemical sector lagged by three months, the price-earnings ratio of the Chemical sector lagged by one month.

Table 32: Correlation Matrix of YoY Chemicals Return, YoY electricity consumption variables of Chemicals, the energy efficiency measures, YoY forward energy price change, YoY carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations YoY Chemicals

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Stock Return	1.000							
(2) Electricity Consumption	0.088	1.000						
(3) Energy Intensity value added	-0.483	0.169	1.000					
(4) CO2 Intensity value added	-0.539	0.224	0.897	1.000				
(5) Fwd Energy Price	0.159	0.421	0.067	0.142	1.000			
(6) CO2 Price	0.480	0.078	-0.223	-0.219	0.265	1.000		
(7) Book-to-Market	-0.578	-0.015	0.493	0.728	-0.227	-0.310	1.000	
(8) Price-Earnings	-0.069	-0.520	-0.208	-0.200	-0.132	0.012	-0.060	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Chemical sector corrected for inflation, the year-over-year change of the electricity consumption of the Chemical sector lagged by one month, the value-added energy intensity of the Chemical sector lagged by one month, the value-added CO2 emissions intensity of the Chemical sector lagged by one month, the year-over-year change in forward energy price lagged by one month, , the year-over-year change in carbon permits' price lagged by one month, the book-to-market ratio of the Chemical sector lagged by one month, the price-earnings ratio of the Chemical sector lagged by one month.

SWEDEN:

Basic Resources:

Table 60: Correlation Matrix of MoM Basic Resources Return, MoM electricity consumption variables of Basic Resources sector, the energy efficiency measures and MoM forward energy price change.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Stock Return	1.000					
(2) Electricity Consumption	0.187	1.000				
(3) Energy Intensity value added	0.056	0.170	1.000			
(4) Energy Intensity	-0.155	0.195	0.596	1.000		
(5) CO2 Intensity	-0.170	0.198	0.513	0.989	1.000	
(6) Fwd Energy Price	-0.099	0.080	0.056	0.274	0.292	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Swedish Basic Resources sector corrected for inflation, the month-over-month change of the electricity consumption of the Basic Resources sector lagged by three months, the value-added energy intensity of the Primary Metals sector lagged by three months, the physical energy intensity of the Steel sector lagged by three months, the physical CO2 emissions intensity of the Steel sector lagged by three months, the month-over-month change in forward energy price lagged by three months.

Table 61: Correlation Matrix of YoY Basic Resources Return, YoY electricity consumption variables of Basic Resources sector, the energy efficiency measures and YoY forward energy price change.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Stock Return	1.000					
(2) Electricity Consumption	0.209	1.000				
(3) Energy Intensity value added	0.295	0.001	1.000			
(4) Energy Intensity	0.165	0.042	0.777	1.000		
(5) CO2 Intensity	0.180	0.118	0.752	0.993	1.000	
(6) Fwd Energy Price	0.098	0.342	0.131	0.225	0.280	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Swedish Basic Resources sector corrected for inflation, the year-over-year change of the electricity consumption of the Basic Resources sector lagged by one month, the value-added energy intensity of the Primary Metals sector lagged by one month, the physical energy intensity of the Steel sector lagged by one month, the physical CO2 emissions intensity of the Steel sector lagged by one month, the year-over-year forward energy price change lagged by one month.

Construction & Materials:

Table 62: Correlation Matrix of MoM Construction & Materials Return, MoM electricity consumption of Construction & Materials sector, the energy efficiency measures, MoM forward energy price change.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Stock Return	1.000					
(2) Electricity Consumption	0.147	1.000				
(3) Energy Intensity value added	-0.056	0.034	1.000			
(4) Energy Intensity	-0.162	0.021	0.726	1.000		
(5) CO2 Intensity	-0.170	0.002	0.604	0.822	1.000	
(6) Fwd Energy Price	-0.105	0.036	0.205	0.318	0.273	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Swedish Construction & Materials sector corrected for inflation, the month-over-month change of the electricity consumption of the Construction & Materials sector lagged by four months, the value-added energy intensity of the Non-Metallic Mineral sector lagged by four months, the physical electricity intensity of the Cement sector lagged by four months, the physical CO2 emissions intensity of the Cement sector lagged by four months, the month-over-month change in forward energy price lagged by four months.

Table 63: Correlation Matrix of YoY Construction & Materials Stock Return, YoY electricity consumption of Construction & Materials sector, the energy efficiency measures, YoY forward energy price change.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Stock Return	1.000					
(2) Electricity Consumption	-0.074	1.000				
(3) Energy Intensity value added	0.359	0.186	1.000			
(4) Energy Intensity	0.036	0.251	0.839	1.000		
(5) CO2 Intensity	-0.055	0.204	0.692	0.821	1.000	
(6) Fwd Energy Price	0.190	0.092	0.070	0.194	0.213	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Construction & Materials sector corrected for inflation, the year-over-year change of the electricity consumption of the Construction & Materials sector lagged by one month, the value-added energy intensity of the Non-Metallic Mineral sector lagged by one month, the physical electricity intensity of the Cement sector lagged by one month, the physical CO2 emissions intensity of the Cement sector lagged by one month, the year-over-year change in forward energy price change lagged by one month.

Chemicals:

Table 64: Correlation Matrix of MoM Chemicals Stock Return, MoM electricity consumption of Chemicals sector, the energy efficiency measures, MoM forward energy price change.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) Stock Return	1.000				
(2) Electricity Consumption	0.191	1.000			
(3) Energy Intensity value added	-0.081	0.024	1.000		
(4) CO2 Intensity	-0.012	0.011	0.714	1.000	
(5) Fwd Energy Price	0.203	0.139	-0.078	0.004	1.000

The table describes the correlations between the following variables: the month-over-month stock return of the Swedish Chemical sector corrected for inflation, the month-over-month change of the electricity consumption of the Chemical sector lagged by six months, the value-added energy intensity of the Chemical sector lagged by six months, the value-added CO2 emissions intensity of the Chemical sector lagged by six months, the month-over-month change in forward energy price lagged by one month.

Table 65: Correlation Matrix of YoY Chemicals Return, YoY electricity consumption variables of Chemicals, the energy efficiency measures, YoY forward energy price change, YoY carbon permits' price change and book-to-market and price-earnings ratios.

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) Stock Return	1.000				
(2) Electricity Consumption	0.056	1.000			
(3) Energy Intensity value added	-0.043	0.211	1.000		
(4) CO2 Intensity	0.143	0.112	0.718	1.000	
(5) Fwd Energy Price	0.117	-0.048	0.075	0.257	1.000

The table describes the correlations between the following variables: the year-over-year stock return of the Chemical sector corrected for inflation, the year-over-year change of the electricity consumption of the Chemical sector lagged by one month, the value-added energy intensity of the Chemical sector lagged by one month, the value-added CO2 emissions intensity of the Chemical sector lagged by one month, the year-over-year change in forward energy price lagged by one month.

APPENDIX C

Table 33: OLS Regressions: MoM Basic Resources Return against the lags of MoM Electricity Consumption of Steel sector.

Y_t is MoM Basic Resources Stock Return at time *t*,

$x_{MoMECS(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Steel sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	-0.138					
	(0.224)					
Electricity Consumption lag2		-0.149				
		(0.194)				
Electricity Consumption lag3			0.0987			
			(0.389)			
Electricity Consumption lag4				-0.136		
				(0.237)		
Electricity Consumption lag5					-0.0410	
					(0.723)	
Electricity Consumption lag6						0.560^{***}
						(0.000)
Constant	0.00705	0.00663	-0.0143	0.00499	-0.00316	-0.0513^{***}
	(0.575)	(0.601)	(0.262)	(0.696)	(0.805)	(0.000)
N	124	124	124	124	124	124
adj. R^2	0.004	0.006	-0.002	0.003	-0.007	0.137
F	1.494	1.704	0.749	1.412	0.126	20.47
p	0.224	0.194	0.389	0.237	0.723	**0.0000141*****
df_r	122	122	122	122	122	122

p-values in parentheses
$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Basic Resources stock return on the lags from one to six months of month-over-month electricity consumption of Steel sector. Sample period: Feb 2010 – May 2020.

Table 34: OLS Regressions: MoM Basic Resources Stock Return against the lags of MoM Electricity consumption of Steel and MoM Electricity Consumption of Nonferrous Metals sector.

Y_t is MoM Basic Resources Stock Return at time *t*,

$x_{MoMECS(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Steel sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6);

$x_{MoMECM(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Nonferrous Metals sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6);

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-i)} + \beta_2 x_{MoMECM(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption Steel_lag1	-0.136 (0.238)					
Electricity Consumption NFMetals_lag1	-0.0128 (0.923)					
Electricity Consumption Steel lag2		-0.127 (0.271)				
Electricity Consumption NFMetals lag2		-0.150 (0.260)				
Electricity Consumption Steel lag3			0.112 (0.335)			
Electricity Consumption NFMetals lag3			-0.0947 (0.478)			
Electricity Consumption Steel lag4				-0.134 (0.254)		
Electricity Consumption NFMetals lag4				-0.0172 (0.898)		
Electricity Consumption Steel lag5					-0.0285 (0.808)	
Electricity Consumption NFMetals lag5					-0.0885 (0.512)	
Electricity Consumption Steel lag6						0.564*** (0.000)
Electricity Consumption NFMetals lag6						-0.0290 (0.842)
Constant	0.00690 (0.587)	0.00487 (0.702)	-0.0154 (0.231)	0.00479 (0.711)	-0.00420 (0.746)	-0.0516*** (0.000)
N	124	124	124	124	124	124
adj. R^2	-0.004	0.008	-0.006	-0.005	-0.012	0.130
F	0.745	1.495	0.626	0.708	0.279	10.18
p	0.477	0.228	0.537	0.494	0.757	**0.0000822*** **
df_r	121	121	121	121	121	121

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Basic Resources return corrected for inflation on the lags from one to six months of month-over-month electricity consumption of the Steel sector and of month-over-month electricity consumption of the Non-ferrous Metals sector. Sample period: Feb 2010 – May 2020.

Table 35: OLS Regressions: MoM Construction & Materials Stock Return against the lags of MoM Electricity Consumption of Cement sector.

Y_t is MoM Construction & Materials Stock Return at time t,

$x_{MoMECCem(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Cement sector at time (t-i) where i is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	0.0148					
	(0.547)					
Electricity Consumption lag2		-0.0259				
		(0.288)				
Electricity Consumption lag3			0.0449*			
			(0.065)			
Electricity Consumption lag4				-0.0371		
				(0.122)		
Electricity Consumption lag5					-0.0240	
					(0.322)	
Electricity Consumption lag6						0.0523**
						(0.031)
Constant	0.00513	0.00561	0.00362	0.00723	0.00648	0.00454
	(0.455)	(0.411)	(0.593)	(0.281)	(0.338)	(0.501)
N	124	124	124	124	124	124
adj. R^2	-0.005	0.001	0.020	0.011	-0.000	0.030
F	0.365	1.139	3.465	2.422	0.989	4.746
p	0.547	0.288	**0.0651***	0.122	0.322	**0.0313****
df r	122	122	122	122	122	122

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Construction & Materials stock return corrected for inflation on the lags from one to six months of month-over-month electricity consumption of Cement sector. Sample period: Feb 2010 – May 2020.

Table 36: OLS Regressions: MoM Chemicals Return against the lags of MoM Electricity Consumption of Chemical sector.

Y_t is MoM Chemicals Stock Return at time *t*,

$x_{MoMECChem(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Chemicals sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1\, x_{MoMECChem(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	-0.382**					
	(0.048)					
Electricity Consumption lag2		0.103				
		(0.596)				
Electricity Consumption lag3			0.228			
			(0.237)			
Electricity Consumption lag4				-0.00310		
				(0.987)		
Electricity Consumption lag5					-0.182	
					(0.340)	
Electricity Consumption lag6						0.149
						(0.438)
Constant	0.00195	0.0000281	0.000211	0.00285	0.00264	0.00266
	(0.794)	(0.997)	(0.978)	(0.703)	(0.722)	(0.722)
N	124	124	124	124	124	124
adj. R^2	0.024	-0.006	0.003	-0.008	-0.001	-0.003
F	3.989	0.282	1.411	0.000263	0.917	0.606
p	**0.048****	0.596	0.237	0.987	0.340	0.438
df_r	122	122	122	122	122	122

p-values in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Chemicals stock return corrected for inflation on the lags from one to six months of month-over-month electricity consumption of Chemicals sector. Sample period: Feb 2010 – May 2020.

Table 38: OLS Regressions: MoM Stock Returns of the Basic Resources sector against MoM Electricity Consumption of the Steel sector and the lags of MoM forward energy price change.

Y_t is MoM Basic Resources Stock Return at time *t*,

$x_{MoMECS(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of the Steel sector at time (*t-6);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_2 x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.566***	0.560***	0.559***	0.558***	0.560***	0.561***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fwd Energy Price lag1	0.0984					
	(0.429)					
Fwd Energy Price lag2		0.0147				
		(0.906)				
Fwd Energy Price lag3			-0.0594			
			(0.633)			
Fwd Energy Price lag4				0.0573		
				(0.646)		
Fwd Energy Price lag5					-0.129	
					(0.301)	
Fwd Energy Price lag6						0.0435
						(0.728)
Constant	-0.0517***	-0.0513***	-0.0511***	-0.0510***	-0.0513***	-0.0513***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	124	124	124	124	124	124
adj. R^2	0.134	0.130	0.131	0.131	0.137	0.130
F	10.52	10.16	10.29	10.28	10.78	10.22
p	**0.0000612*****	**0.0000833*****	**0.0000748*****	**0.0000754*****	**0.0000490*****	**0.0000789*****
df_r	121	121	121	121	121	121

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Basic Resources stock return corrected for inflation, the month-over-month electricity consumption of the Steel sector lagged by six months, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2010 – May 2020.

Table 39: OLS Regressions: MoM Stock Returns of the Basic Resources sector against MoM Electricity Consumption of the Steel sector and the lags of MoM carbon permits' price change.

Y_t is MoM Basic Resources Stock Return at time *t*,

$x_{MoMECS(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of the Steel sector at time *(t-6);*

$x_{MoMPCO2(t-i)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time *(t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-6)} + \beta_2 x_{MoMPCO2(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.563***	0.562***	0.561***	0.560***	0.558***	0.562***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CO2 Price lag1	-0.0424					
	(0.606)					
CO2 Price lag2		-0.0377				
		(0.646)				
CO2 Price lag3			0.0889			
			(0.277)			
CO2 Price lag4				-0.0183		
				(0.823)		
CO2 Price lag5					0.103	
					(0.209)	
CO2 Price lag6						0.0619
						(0.449)
Constant	-0.0509***	-0.0509***	-0.0525***	-0.0510***	-0.0525***	-0.0523***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	124	124	124	124	124	124
adj. R^2	0.131	0.131	0.138	0.130	0.141	0.134
F	10.31	10.28	10.85	10.18	11.09	10.49
p	**0.0000734***	**0.0000754***	**0.0000464***	**0.0000818***	**0.0000380***	**0.0000629***
df_r	121	121	121	121	121	121

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Basic Resources stock return corrected for inflation, the month-over-month electricity consumption of the Steel sector lagged by six months, the lags from one to six months of month-over-month carbon permits' price change. Sample period: Feb 2010 – May 2020.

Table 40: OLS Regressions: MoM Stock Returns of the Construction & Materials sector against MoM Electricity Consumption of the Cement sector and the lags of MoM forward energy price change.

Y_t is MoM Construction & Materials Stock Return at time *t*,

$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of the Cement sector at time (*t-3);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.0453*	0.0449*	0.0444*	0.0445*	0.0441*	0.0438*
	(0.064)	(0.066)	(0.069)	(0.067)	(0.071)	(0.069)
Fwd Energy Price lag1	-0.0230					
	(0.814)					
Fwd Energy Price lag2		-0.00637				
		(0.948)				
Fwd Energy Price lag3			-0.0671			
			(0.492)			
Fwd Energy Price lag4				-0.114		
				(0.239)		
Fwd Energy Price lag5					-0.0816	
					(0.402)	
Fwd Energy Price lag6						0.0568
						(0.554)
	0.00360	0.00362	0.00363	0.00366	0.00366	0.00497
Constant	(0.596)	(0.595)	(0.593)	(0.589)	(0.590)	(0.460)
N	124	124	124	124	124	123
adj. R^2	0.012	0.012	0.015	0.023	0.017	0.014
F	1.747	1.721	1.963	2.437	2.083	1.865
p	0.179	0.183	0.145	0.0917*	0.129	0.159
df_r	121	121	121	121	121	120

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Construction & Materials stock return corrected for inflation, the month-over-month electricity consumption of the Cement sector lagged by three months, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2010 – May 2020.

Table 41: OLS Regressions: MoM Stock Returns of the Construction & Materials sector against MoM Electricity Consumption of the Cement sector and the lags of MoM carbon permits' price change.

Y_t is MoM Construction & Materials Stock Return at time t,

$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of the Cement sector at time (*t-3);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1\, x_{MoMECCem(t-3)} + \beta_2\, x_{MoMPCO2(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.0445*	0.0450*	0.0450*	0.0449*	0.0433*	0.0419*
	(0.066)	(0.066)	(0.066)	(0.066)	(0.072)	(0.083)
CO2 Price lag1	0.0922					
	(0.149)					
CO2 Price lag2		-0.0118				
		(0.854)				
CO2 Price lag3			0.0261			
			(0.684)			
CO2 Price lag4				-0.00744		
				(0.908)		
CO2 Price lag5					-0.0360	
					(0.568)	
CO2 Price lag6						0.0509
						(0.422)
Constant	0.00239	0.00379	0.00326	0.00373	0.00552	0.00480
	(0.726)	(0.581)	(0.635)	(0.587)	(0.416)	(0.481)
N	124	124	124	124	123	122
adj. R^2	0.029	0.012	0.013	0.012	0.014	0.017
F	2.805	1.736	1.804	1.725	1.852	2.015
p	0.0644*	0.181	0.169	0.182	0.161	0.138
df_r	121	121	121	121	120	119

p-values in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Construction & Materials stock return corrected for inflation, the month-over-month electricity consumption of the Cement sector lagged by three months, the lags from one to six months of month-over-month carbon permits' price change. Sample period: Feb 2010 – May 2020.

Table 42: OLS Regressions: MoM Stock Returns of the Chemicals sector against MoM Electricity Consumption of the Chemicals sector and the lags of MoM forward energy price change.

Y_t is MoM Chemicals Stock Return at time *t*,

$x_{MoMECChem(t-1)}$ is MoM Seasonally Adjusted Electricity Consumption of the Chemicals sector at time *(t-1);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time *(t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-1)} + \beta_2 x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	-0.383**	-0.385**	-0.359*	-0.366*	-0.432**	-0.278
	(0.048)	(0.050)	(0.068)	(0.068)	(0.027)	(0.186)
Fwd Energy Price lag1	-0.0188					
	(0.862)					
Fwd Energy Price lag2		0.0125				
		(0.909)				
Fwd Energy Price lag3			0.0703			
			(0.523)			
Fwd Energy Price lag4				-0.00243		
				(0.983)		
Fwd Energy Price lag5					-0.221**	
					(0.043)	
Fwd Energy Price lag6						0.0369
						(0.737)
Constant	0.00195	0.00195	0.00189	0.00120	0.00159	0.00212
	(0.795)	(0.795)	(0.801)	(0.874)	(0.831)	(0.780)
N	124	124	124	123	122	121
adj. R^2	0.016	0.016	0.019	0.013	0.047	-0.002
F	1.994	1.985	2.190	1.819	3.951	0.890
p	0.141	0.142	0.116	0.167	**0.0218****	0.413
df r	121	121	121	120	119	118

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Chemicals stock return corrected for inflation, the month-over-month electricity consumption of the Chemicals sector lagged by one month, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2010 – May 2020.

Table 43: OLS Regressions: MoM Stock Returns of the Chemicals sector against MoM Electricity Consumption of the Chemicals sector and the lags of MoM carbon permits' price change.

Y_t is MoM Chemicals Stock Return at time *t*,

$x_{MoMECChem(t-1)}$ is MoM Seasonally Adjusted Electricity Consumption of the Chemicals sector at time (*t-1);*

$x_{MoMPCO2(t-i)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-1)} + \beta_2 x_{MoMPCO2(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	-0.418**	-0.404**	-0.297	-0.348*	-0.262	-0.278
	(0.031)	(0.038)	(0.119)	(0.073)	(0.205)	(0.178)
CO2 Price lag1	0.106					
	(0.138)					
CO2 Price lag2		0.0628				
		(0.381)				
CO2 Price lag3			0.178**			
			(0.012)			
CO2 Price lag4				-0.0892		
				(0.211)		
CO2 Price lag5					-0.0246	
					(0.729)	
CO2 Price lag6						0.0348
						(0.625)
Constant	0.000549	0.00110	-0.00155	0.00258	0.00247	0.000898
	(0.942)	(0.884)	(0.835)	(0.735)	(0.747)	(0.907)
N	124	124	123	122	121	120
adj. R^2	0.033	0.022	0.064	0.026	-0.002	0.001
F	3.127	2.377	5.177	2.613	0.894	1.053
p	0.0474	0.0971	**0.00697*** **	0.0775	0.412	0.352
df r	121	121	120	119	118	117

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Chemicals stock return corrected for inflation, the month-over-month electricity consumption of the Chemicals sector lagged by one month, the lags from one to six months of month-over-month carbon permits' price change. Sample period: Feb 2010 – May 2020.

Table 45: OLS Regressions: MoM Stock Returns of Construction & Materials sector against the MoM Electricity of Cement sector, energy efficiency measure (CO2 intensity), forward energy price change and carbon permits' price change.

Y_t is MoM Construction & Materials Stock Return at time *t*,
$x_{MoMECCem(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Cement sector at time (*t-3)*;
$x_{CO2Cement(t-3)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-3)*;
$x_{MoMEP(t-4)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-4);*
$x_{MoMPCO2(t-1)}$ is MoM Seasonally Adjusted Carbon Permits' Price variation at time (*t-1).*

Model 1: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{CO2Cement(t-3)} + \beta_3 x_{MoMEP(t-4)} + \beta_4 x_{MoMPCO2(t-1)} + \varepsilon_t$

	(1) Construction Materials Stock Return
Electricity Consumption Cement	0.320***
	(0.001)
CO2 Intensity Cement	0.266*
	(0.079)
Fwd Energy Price	-0.154
	(0.106)
CO2 Price	0.0752
	(0.223)
Constant	-0.0578*
	(0.066)
N	119
adj. R^2	0.106
F	4.498
p	0.00207
df_r	114

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month stock return of the Construction & Materials sector corrected for inflation, the month-over-month change of the electricity consumption of the Cement sector lagged by three months, the CO2 emissions intensity of the Cement sector, the month-over-month forward energy price change lagged by four months, the month-over-month carbon permits' price change lagged by one month . The Sample period: Feb 2010 – May 2020.

Table 46: OLS Regressions: YoY Stock Returns of the Construction & Materials sector against the lags of the YoY Electricity Consumption of the Cement sector.

Y_t is YoY Chemicals Stock Return at time t,

$x_{YoYECCem(t-1)}$ is YoY Electricity Consumption of the Cement sector at time $(t\text{-}i)$ where i is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{YoYECCem(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	-0.147					
	(0.427)					
Electricity Consumption lag2		-0.216				
		(0.242)				
Electricity Consumption lag3			-0.157			
			(0.395)			
Electricity Consumption lag4				-0.284		
				(0.123)		
Electricity Consumption lag5					-0.222	
					(0.230)	
Electricity Consumption lag6						-0.227
						(0.219)
Constant	0.0591^{**}	0.0552^{**}	0.0611^{**}	0.0537^{**}	0.0569^{**}	0.0563^{**}
	(0.027)	(0.038)	(0.022)	(0.042)	(0.033)	(0.034)
N	113	113	113	113	113	113
adj. R^2	-0.003	0.003	-0.002	0.013	0.004	0.005
F	0.637	1.382	0.730	2.419	1.456	1.526
p	0.427	0.242	0.395	0.123	0.230	0.219
df r	111	111	111	111	111	111

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the year-over-year Construction & Materials stock return corrected for inflation, the lags from one to six months of the year-over-year electricity consumption of the Cement sector. Sample period: Feb 2011– May 2020.

Table 49: OLS Regressions: YoY Stock Returns of Basic Resources sector against the YoY Electricity of Steel sector with energy efficiency measure (CO2 intensity), forward energy price change.

Y_t is YoY Construction & Materials Stock Return at time *t*,
$x_{YoYECCem(t-1)}$ is YoY Electricity Consumption of Cement sector at time (*t-1)*;
$x_{CO2Cement(t-1)}$ is the Intensity of CO2 emissions of Cement sector (tCO2/t) at time (*t-1)*;
$x_{YoYEP(t-1)}$ is the YoY Forward Energy Price variation at the MTE market at time (*t-1).*

Model 1: $Y2_t = \beta_0 + \beta_1 x_{YoYECCem(t-1)} + \beta_2 x_{CO2Cement(t-1)} + \beta_3 x_{YoYEP(t-1)} + \varepsilon_t$

	(1) Basic Resources Stock Return
Electricity Consumption	0.560**
	(0.025)
CO2 Intensity	0.502***
	(0.002)
Fwd Energy Price	0.183
	(0.111)
Constant	-0.363***
	(0.001)
N	113
adj. R^2	0.181
F	9.225
p	**0.0000172*** **
df_r	109

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the year-over-year stock return of the Basic Resources sector corrected for inflation, the year-over-year change of the electricity consumption of the Steel sector lagged by one month, the CO2 emissions intensity of Steel sector lagged by one month, the year-over-year forward energy price change lagged by one month, the year-over-year carbon permits' price change lagged by one month. The Sample period: Feb 2011 – May 2020.

Table 66: OLS Regressions: MoM Swedish Basic Resources Stock Return against the lags of MoM Electricity Consumption of Basic Resources sector.

Y_t is MoM Basic Resources Stock Return at time t,

$x_{MoMECS(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Basic Resources sector at time (t-i) where i is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 \, x_{MoMECS(t-i)} + \varepsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	Stock Return	Stock Return	Stock Return	Stock Return	Stock Return	Stock Return
Electricity Consumption lag1	0.0492					
	(0.743)					
Electricity Consumption lag2		-0.0667				
		(0.658)				
Electricity Consumption lag3			0.320**			
			(0.026)			
Electricity Consumption lag4				-0.204		
				(0.155)		
Electricity Consumption lag5					0.00310	
					(0.983)	
Electricity Consumption lag6						0.0637
						(0.658)
Constant	0.0136**	0.0148***	0.00962*	0.0140**	0.0123**	0.0111**
	(0.017)	(0.010)	(0.073)	(0.010)	(0.025)	(0.043)
N	153	153	153	152	151	150
adj. R^2	-0.006	-0.005	0.026	0.007	-0.007	-0.005
F	0.108	0.197	5.088	2.048	0.000461	0.197
p	0.743	0.658	**0.0255****	0.155	0.983	0.658
df r	151	151	151	150	149	148

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Basic Resources stock return on the lags from one to six months of month-over-month electricity consumption of Basic Resources sector. Sample period: Feb 2009 – Oct 2021.

Table 67: OLS Regressions: MoM Swedish Construction & Materials Stock Return against the lags of MoM Electricity Consumption of Construction & Materials sector.

Y_t is MoM Construction & Materials Stock Return at time *t*,

$x_{MoMECCem(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Construction & Materials sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECCem(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	0.0412					
	(0.597)					
Electricity Consumption lag2		-0.0389				
		(0.620)				
Electricity Consumption lag3			-0.0356			
			(0.626)			
Electricity Consumption lag4				0.130^{*}		
				(0.075)		
Electricity Consumption lag5					-0.0119	
					(0.872)	
Electricity Consumption lag6						-0.0846
						(0.244)
Constant	0.0133^{***}	0.0135^{***}	0.0119^{***}	0.0109^{**}	0.0118^{***}	0.0114^{***}
	(0.004)	(0.003)	(0.006)	(0.011)	(0.007)	(0.008)
N	137	136	135	134	133	132
adj. R^2	-0.005	-0.006	-0.006	0.016	-0.007	0.003
F	0.281	0.248	0.239	3.216	0.0262	1.372
p	0.597	0.620	0.626	0.0752*	0.872	0.244
df r	135	134	133	132	131	130

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Construction & Materials stock return corrected for inflation on the lags from one to six months of month-over-month electricity consumption of Cement sector. Sample period: Feb 2009 – Jul 2020.

Table 68: OLS Regressions: MoM Swedish Chemicals Return against the lags of MoM Electricity Consumption of Chemical sector.

Y_t is MoM Chemicals Stock Return at time *t*,

$x_{MoMECChem(t-i)}$ is MoM Seasonally Adjusted Electricity Consumption of the Chemicals sector at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption lag1	-0.320					
	(0.172)					
Electricity Consumption lag2		0.0948				
		(0.687)				
Electricity Consumption lag3			-0.0434			
			(0.848)			
Electricity Consumption lag4				0.168		
				(0.454)		
Electricity Consumption lag5					-0.00751	
					(0.974)	
Electricity Consumption lag6						0.492**
						(0.029)
Constant	0.0254***	0.0247***	0.0225***	0.0214***	0.0217***	0.0206***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)
N	137	136	135	134	133	132
adj. R^2	0.006	-0.006	-0.007	-0.003	-0.008	0.029
F	1.888	0.163	0.0370	0.563	0.00109	4.879
p	0.172	0.687	0.848	0.454	0.974	**0.0289****
df r	135	134	133	132	131	130

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Chemicals stock return corrected for inflation on the lags from one to six months of month-over-month electricity consumption of Chemicals sector. Sample period: Feb 2009 – Jul 2020.

Table 69: OLS Regressions: MoM Swedish Stock Returns of the Basic Resources sector against MoM Electricity Consumption of the Basic Resources sector and the lags of MoM forward energy price change.

Y_t is MoM Basic Resources Stock Return at time *t*,

$x_{MoMECS(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of the Basic Resources sector at time (*t-3);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECS(t-3)} + \beta_2 x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.322**	0.321**	0.325**	0.317**	0.313**	0.332**
	(0.025)	(0.026)	(0.023)	(0.026)	(0.029)	(0.020)
Fwd Energy Price lag1	0.0180					
	(0.828)					
Fwd Energy Price lag2		-0.0115				
		(0.905)				
Fwd Energy Price lag3			-0.0736			
			(0.451)			
Fwd Energy Price lag4				-0.0374		
				(0.700)		
Fwd Energy Price lag5					0.00760	
					(0.940)	
Fwd Energy Price lag6						0.0607
						(0.547)
Constant	0.00954*	0.00962*	0.00964*	0.00893*	0.00929*	0.00841
	(0.078)	(0.074)	(0.073)	(0.096)	(0.085)	(0.117)
N	153	153	153	152	151	150
adj. R^2	0.020	0.020	0.023	0.021	0.019	0.027
F	2.552	2.535	2.823	2.639	2.465	3.028
p	0.0813*	0.0827*	0.0626*	0.0748*	0.0885*	0.0514*
df_r	150	150	150	149	148	147

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Basic Resources stock return corrected for inflation, the month-over-month electricity consumption of the Basic Resources sector lagged by three months, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2009 – Oct 2021.

Table 70: OLS Regressions: MoM Stock Returns of the Swedish Construction & Materials sector against MoM Electricity Consumption of the Construction & Materials sector and the lags of MoM forward energy price change.

Y_t is MoM Construction & Materials Stock Return at time *t*,

$x_{MoMECCem(t-4)}$ is MoM Seasonally Adjusted Electricity Consumption of the Construction & Materials sector at time (*t-4);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1\, x_{MoMECCem(t-4)} + \beta_2\, x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.128*	0.132*	0.126*	0.133*	0.130*	0.116
	(0.083)	(0.071)	(0.083)	(0.068)	(0.078)	(0.109)
Fwd Energy Price lag1	0.0212					
	(0.801)					
Fwd Energy Price lag2		0.0751				
		(0.372)				
Fwd Energy Price lag3			-0.0955			
			(0.255)			
Fwd Energy Price lag4				-0.113		
				(0.179)		
Fwd Energy Price lag5					0.00233	
					(0.978)	
Fwd Energy Price lag6						0.0783
						(0.363)
Constant	0.0110**	0.0112***	0.0105**	0.0104**	0.0109**	0.0105**
	(0.011)	(0.009)	(0.014)	(0.014)	(0.012)	(0.014)
N	134	134	134	134	133	132
adj. R^2	0.009	0.015	0.019	0.022	0.009	0.012
F	1.629	2.008	2.266	2.529	1.581	1.784
p	0.200	0.138	0.108	0.0836*	0.210	0.172
df_r	131	131	131	131	130	129

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Construction & Materials stock return corrected for inflation, the month-over-month electricity consumption of the Construction & Materials sector lagged by four months, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2009 – Jul 2020.

Table 71: OLS Regressions: MoM Stock Returns of the Swedish Chemicals sector against MoM Electricity Consumption of the Chemicals sector and the lags of MoM forward energy price change.

Y_t is MoM Chemicals Stock Return at time *t*,

$x_{MoMECChem(t-6)}$ is MoM Seasonally Adjusted Electricity Consumption of the Chemicals sector at time (*t-6);*

$x_{MoMPE(t-i)}$ is MoM Seasonally Adjusted Forward Energy Price variation at the MTE market at time (*t-i)* where *i* is the number of months of delay (from 1 to 6).

Model: $Y_t = \beta_0 + \beta_1 x_{MoMECChem(t-6)} + \beta_2 x_{MoMPE(t-i)} + \varepsilon_t$

	(1) Stock Return	(2) Stock Return	(3) Stock Return	(4) Stock Return	(5) Stock Return	(6) Stock Return
Electricity Consumption	0.430*	0.494**	0.453**	0.488**	0.490**	0.493**
	(0.055)	(0.029)	(0.040)	(0.031)	(0.030)	(0.029)
Fwd Energy Price lag1	0.305**					
	(0.037)					
Fwd Energy Price lag2		-0.0185				
		(0.901)				
Fwd Energy Price lag3			-0.385***			
			(0.008)			
Fwd Energy Price lag4				-0.0408		
				(0.783)		
Fwd Energy Price lag5					0.0874	
					(0.554)	
Fwd Energy Price lag6						-0.0169
						(0.911)
Constant	0.0219***	0.0205***	0.0190***	0.0205***	0.0209***	0.0205***
	(0.003)	(0.007)	(0.010)	(0.007)	(0.006)	(0.006)
N	132	132	132	132	132	132
adj. R^2	0.054	0.021	0.073	0.022	0.024	0.021
F	4.716	2.429	6.172	2.460	2.603	2.427
p	**0.0105****	0.0922*	**0.00276*****	0.0894*	0.0779*	0.0923*
df_r	129	129	129	129	129	129

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The Table describes the results of the OLS regressions performed on the following variables: the month-over-month Swedish Chemicals stock return corrected for inflation, the month-over-month electricity consumption of the Chemicals sector lagged by six months, the lags from one to six months of month-over-month forward energy price change. Sample period: Feb 2009 – Jul 2020.

Table 74: OLS Regressions: MoM Stock Returns of Swedish Basic Resources and Swedish Construction & Materials sector against their MoM Electricity Consumption, energy efficiency measure (physical energy intensity) and forward energy price change.

$Y1_t$ is MoM Swedish Basic Resources Stock Return at time *t*,
$x_{MoMECS(t-3)}$ is MoM Seasonally Adjusted Electricity Consumption of Basic Resources sector at time (*t-3)*;
$x_{UConsS(t-3)}$ is the Intensity of Energy Consumption of Steel sector per ton of production (toe/t) at time (*t-3)*;
$x_{MoMEP(t-3)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at time (*t-3).*

Model 1: $Y1_t = \beta_0 + \beta_1 x_{MoMECCem(t-3)} + \beta_2 x_{UConsS(t-3)} + \beta_3 x_{MoMEP(t-3)} + \varepsilon_t$

$Y2_t$ is MoM Swedish Construction & Materials Stock Return at time *t*,
$x_{MoMECCem(t-4)}$ is MoM Seasonally Adjusted Electricity Consumption of Construction & Materials sector at time (*t-4)*;
$x_{UConsC(t-4)}$ is the Intensity of <u>Electricity</u> Consumption of Cement sector per ton of production (kWh/t) at time (*t-4)*;
$x_{MoMEP(t-4)}$ is the MoM Seasonally Adjusted Forward Energy Price variation at time (*t-4).*

Model 2: $Y2_t = \beta_0 + \beta_1 x_{MoMECCem(t-4)} + \beta_2 x_{UConsC(t-4)} + \beta_3 x_{MoMEP(t-4)} + \varepsilon_t$

	(1) Basic Resources Sweden	(2) Construction & Materials Sweden
Electricity Consumption	0.424***	0.128*
	(0.004)	(0.081)
Energy Intensity	-0.250**	-0.000462
	(0.037)	(0.116)
Fwd Energy Price	-0.0890	-0.0649
	(0.424)	(0.480)
Constant	0.0805**	0.0636*
	(0.026)	(0.064)
N	143	131
adj. R^2	0.063	0.030
F	4.192	2.344
p	**0.0071*** **	0.0761*
df_r	139	127

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table describes the results of the OLS regressions performed on the following variables: the month-over-month stock return of the Swedish Basic Resources sector corrected for inflation, the month-over-month stock return of the Swedish Construction & Materials sector corrected for inflation, the month-over-month change of the electricity consumption of the Basic Resources sector lagged by three months, the month-over-month change of the electricity consumption of the Construction & Materials sector lagged by four months, the physical energy intensity of the Steel sector, the physical electricity intensity of the Cement sector, the month-over-month forward energy price change lagged by three and four months. The Sample period: Feb 2009 – Dec 2020.