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Course of Asset Pricing

How does the Stock Market reflect the Macroeconomic Conditions? Evidence from Italy

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Abstract

The behavior of the stock market is described basically in two main dimensions, that are return and volatility. Understanding the levers for which the market moves has a predominant importance between the entire cluster of market participants, supervisors and policy makers. A smooth functioning of the stock market can not only speed up the economic growth of countries, but also minimize the transaction fees, enhance the financial stability and maintain the essential investment flows throughout the economies benefitting citizens and business.

In this context, several economic studies have previously suggested that stock markets are affected by movements of some macroeconomic variables. Therefore, market modeling by means of those kinds of factors has been examined in the past in different market venues, but the obtained results were often in contrast and important differences still persist depending on the geography and the period taken into consideration for the analysis.

The ambition of this thesis is to investigate whether changes in specific macroeconomic variables suggested by previous literature can cause instantaneous or lagged effects on the performance of the Italian Stock Market (FTSE MIB Index).

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INTRODUCTION

Stock markets are an essential component for soliciting funding for companies and governments willing of financing projects directly from investors. At the same time, they are considered a leading indicator of future economic activity, reflecting expectations about future corporate performances.

A smooth functioning of the stock market can speed up the economic growth of countries, minimize the transaction fees, enhance the financial stability and maintain the essential investment flows throughout the economies benefitting citizens and business. At the opposite, when instabilities or crises occur in these kinds of markets, partial or general crunches may arise in the economy. Therefore, investors, supervisors and policy makers meticulously pay attention to stock market movements in order to take precautions in case of problems.

Even though fluctuations of single stocks may succeed for economic and political questions related to traditional microeconomic factors (Ex. Fama and French - Company dimension, company book-to-market values, stock risk in excess to the market), while investigating the overall performance of the stock market of a country, macroeconomic factors are surely more appropriate.

Under the view of the Dividend Discount Model (DDM) proposed by Miller and Modigliani (1961), the price of a specific asset *i* equals the future expected cash flows discounted:

$$P_{i,t} = \sum_{t=1}^{\infty} \frac{CF_{i,t}}{\left(1 + r_{i,t}\right)^{t}}$$

In this context, the macroeconomic environment is an excellent candidate to be a crucial determinant of stock market pricing, as it is surely qualified to influence contemporaneously cash-flows of a great part of companies and general levels of discount rates.

Given this important potentiality, market modeling by means of domestic and global macroeconomic factors has been examined in the past in different market venues, but the obtained results were sometimes in contrast and important differences still persist depending on the geography and the period taken into consideration for the analysis.

The aim of this thesis is to investigate whether changes in specific global and national macroeconomic variables suggested by previous literature can cause instantaneous or lagged effects on the performance of the Italian Stock Market (FTSE MIB Index).

To succeed in the objective, the research comprehends an initial part of literature review, which is intended to obtain suggestions from previous literature about which macro-factors may exhibit contemporaneous and lagged effects on the stock market, a second chapter where literature hints are empirically verified individually and a final stage in which the most relevant macroeconomic factors are combined in an Explanatory Model and in a Forecasting Model. As a large component of the present literature on the topic (Humpe and Macmilan, 2007), the two models are based on the Arbitrage Pricing Theory (APT), whereby the yield of the Italian Stock Market is explained linearly by a series of macroeconomic factors.

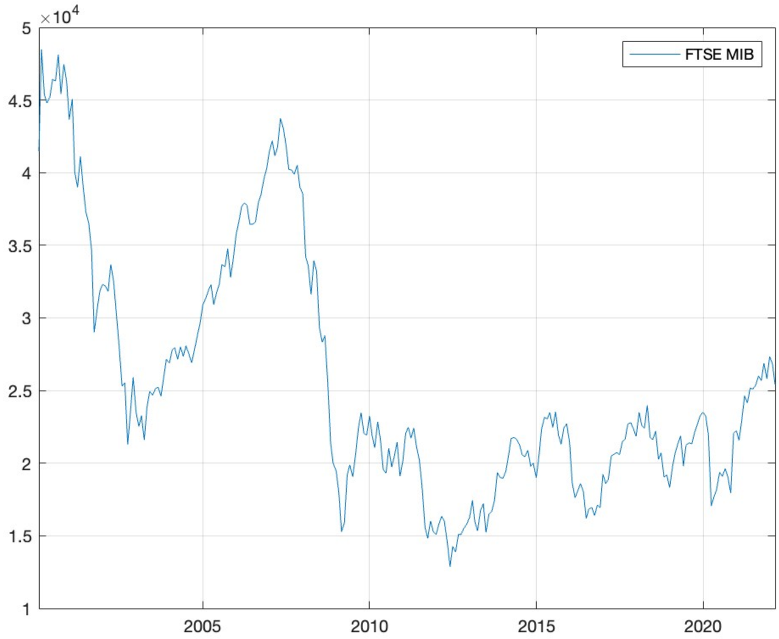
FTSE MIB INDEX

Because of this research is concentrated in discovering macroeconomic factors able to impact present and future returns of the Italian Stock Market, the FTSE MIB Index (Financial Times Stock Exchange Milano Indice di Borsa) has been employed as market benchmark. Consequently, the objective of this spot is to give a brief introduction to such market index.

From June 2009, FTSE MIB is composed by 40 stocks representing about 80% of total Italian market value, chosen between the most liquid and capitalized. Prior of that date, the reference index for Italy was the MIB 30 Index.

From a compositional point of view, the heaviest sectors for capitalization are not remained constant over the time horizon of the analysis. Indeed, nowadays the financial sector accounts for about 15% compared to more than 25% before of the Great Crisis in 2008 and telecommunications, that used to be very influent at the beginning of 2000s (almost 30%), today values less than 2%. At the opposite, industry, luxury and automotive increased continuously in importance during the 2000-2022 period, compensating the loss of capitalization of the other sectors.

Here the price line of the Italian Stock Market from 2000 to February 2022:



The FTSE MIB Index importantly suffered the starting of millennium in the wave of the DOT COM Bubble Crisis exploded in the US and widespread thereafter in Europe, to successively recover almost all losses till 2007. With the default of Lehman Brothers in 2008, a new and more important bearish period begun, also due to the problems Italian Government experienced during the European Sovereign Debt Crisis. Between 2008 and 2012 the market crashed up to 70% and, despite the partial recover of the following years, today pre-crisis levels are still remarkably far.

LITERATURE REVIEW

Through the past few decades, a multitude of researchers, academicians, economists and professionals have continuously investigated and attempted to understand the principal drivers of the stock market, over different geographies and time horizons.

The financial sector holds that price changes are the reflection of the reaction to fresh information about interest rates and company earnings, which, at the same time, are moved by a multitude of other previously disclosed factors.

Under the view of the Dividend Discount Model (DDM) proposed by Miller and Modigliani (1961), the price of a specific asset *i* equals the future expected cash flows discounted:

$$P_{i,t} = \sum_{t=1}^{\infty} \frac{CF_{i,t}}{\left(1 + r_{i,t}\right)^{t}}$$

Consequently, the macroeconomic environment is an excellent candidate to be a crucial determinant of stock pricing, as it is surely qualified to influence contemporaneously the cash-flows of companies and the discount rates.

In a considerable part of the economic theory, some relations are given for granted: interest rates, industrial production growth, inflation, exchange rates, money supply and oil price are all generally considered as linked factors to stock price evolution.

On the other hand, the possibility to forecast prices and returns using public available information is contradictory to the Efficient Market Hypothesis (EMH) (Fama, 1970), in particular with respect to the semi-strong form.

In addition to macroeconomic variables, theory has also suggested other kinds of factors to have a role in pricing and return determination, including social and political ones. Surely, in some circumstances, also speculative and irrational forces may drive the stock values, as famously argued by Keynes (1936), for who investors price stocks based not on their idea about fundamentals, but on their opinion regarding what the other investors think about stock values. The same concept has been expanded by Robert Shiller (2003), 2013 Nobel laureate in Economics and one of the most influential proponents of the Behavioral Finance literature.

A potential excellent way to relate macroeconomic factors and stock returns is to employ the Arbitrage Pricing Theory (APT) (Ross, 1976), whereby the yield of an asset is explained linearly by a series of other factors. A large component of the present literature on the topic is based on the APT theory (Humpe and Macmilan, 2007). Chen, Roll and Ross (1986) were the initial authors employing the APT theory to propose a model based on macroeconomic factors to explain the security returns in the US market. The model presents as:

$$r_{i,t} = \alpha_i + \beta * IP_t + \gamma * EI_t + \delta * UI_t + \theta * RP_t + \varphi * TP_t + \varepsilon_t$$

Where:

IP = Industrial Production growth;

EI = Expected Inflation Change (%);

UI = Unexpected Inflation Change (%);

RP = Excess return of long-term corporate bonds over long-term government bonds;

TP = Excess Return of long-term government bonds over short-term government bonds.

They found a significant correlation between the returns in the US and the selected variables, especially for changes in the Industrial Production, in the Risk Premium and for distortions in the Term Premium.

In an early influential study undertaken by Fama (1981), the effects of macroeconomic factors were extensively researched, finding that several macro-variables seem to have a strong impact on returns and volatilities, whereas others appear to be uncertain.

Gesk and Roll (1983) documented the importance of exchange rates in the determination of stock prices, because of the repercussions on the balance of trade. In particular, a depreciation of the exchange rate would boost the export and, therefore, the net cash flows for home companies that would trigger an increase in stock prices. Sun and Tong (2000), Tourani-Rad, Choi and Wilson (2006) and Bloom (2020) indicated the same conclusions.

For Maysami, Howe & Hamzah (2004) the significance of the exchange as factor would largely depend on the grade of international trade and on the trade balance, suggesting a serious impact for those economies founded on international exchanges. The effects over the market volatility were examined by Hasan and Zaman (2017), who found a significant positive relationship with an increase of the exchange rate.

An influential school of thought supports the idea that oil prices can significantly hit advanced economies (Jones and Kaul, 1996; Sadorsky, 1999; Brown and Yucel, 2002; Sariannidis et al., 2010). Hamilton (1983) exhibited as oil was the cause of seven out of eight recessions in the US after the WWII, since an increase in its cost shrinks the demand side of economies and curtails business earnings. Analogously, Jones and Kaul (1996) showed how either current and lagged oil price are able to involve negatively stock returns in the period between 1947 and 1991 in the US and Canada. By Degiannakis et al. (2014) comes the clue that oil is also a strong predictor of market volatility, in addition to market returns.

About the relationship between inflation and stock market, theory has proven a negative effect (Fama and Schwert, 1977; Geske and Roll, 1983; Chen, Roll and Ross, 1986; Omran and Pointon, 2001). As suggested by the Dividend Discount Model, an increase in the expected inflation rises the nominal risk-free rate and, therefore, the discount rates. This should turn in lower stock prices if company cash flows augment at a lower rate than inflation.

Along the same line of thought, the GDP growth (national, continental and/or global) and its leading levers (e.g., Industrial Production Growth) are primary factors considered in the process of creating expectations about future dividends paid by companies. Several researchers have documented the presence of a significant relationship between GDP growth and stock market return (Oberuc, 2004; Tri, 2005; Acikalin et al., 2008; Pilinkus and Boguslauskas, 2009), implying a positive causality effect. Hamilton and Susmel (1994) and Sinha (1996) through GARCH models concluded that equity volatility is more likely to stay high during recessions (negative GDP growth).

A further substantial impact to stock market has been demonstrated to come from the evolution of the labor market. Plinkus and Boguslauskas (2009), analyzing the short-term relation between stock returns and unemployment in Lithuania through the period between 2000 and 2009, found an inverse link between the two variables. Andersen and Bollerslev (1998) considered the publication of US the non-farm payroll as one of the most significant factors for American stocks, while Lucey et al. (2008) demonstrated a similar influence in Europe, in the UK market. Boyd et al. (2001) evidenced as unemployment news have different consequences for the stock market depending on the business cycle of the economy: a rising in unemployment is associated to good news during economic expansion, because it is a signal of interest rates

decline, and to an adverse disclosure during recessions, since it cuts corporate earnings. Given the economy is usually in an expansion phase, the first situation is more common.
In addition to employment, the labor market manifests its effects in the stock market by way of income level and income growth because, as evidenced by Eita (2012). These factors impact the national level of consumption and, consequently, also the cash-flows of the companies.

Scholars suggest the monetary policy as supplementary considerable factor in pricing. Because of the intrinsic value of stocks is given by the discounted expected cash flows, monetary policy results to influence both discount rates and future dividends, especially over long horizons (Lastrapes, 1998; Rapach, 2001). Moreover, prices tend to be less volatile after jumps due to monetary policy news, compared to jumps triggered by other causes (Bloom, 2021).
Anyway, a major difficulty in employing monetary policy in this framework is dictated by the circumstance that central bankers are significantly constrained in their decisions. As a matter of fact, central banks possess clear objectives of control over inflation, employment and output levels. Consequently, there is a substantial interdependence not only between the monetary policy and the other risk factors, but also with the stock market itself, since bankers cannot avoid chasing the latter in the process of adopting their decisions (Rigobon and Sack, 2003). Hence, a reverse causation problem cannot be ignored in evaluating the effects of the policy over financial markets (Bjørnland and Leitemo, 2009).

A somewhat recent argument in finance indicates to consider in company evaluation the Environmental, Social and Governance (ESG) developments as novel risk factors, more particularly in Europe. Policy makers, regulators, consumers and the financial industry in general, in fact, have considerably enhanced the importance entrusted in this kind of factors in the last years. Companies are now forced to consider ESG topics in their business (La Torre, Mango, Cafaro and Leo, 2020). Gloßner (2018) proved as ignoring ESG risks affect negatively returns, whereas Giese and Nagy (2018) constructed a multifactor model considering ESG factors in stock evaluation. In general, empirical research is uniform is stating how the non-consideration of sustainability impacts negatively financial performances, although the debate is still unsolved regarding the possibility of a positive influence, suggesting the existence of an asymmetric effect for ESG factors.

More possible clues concerning the relationship between macroeconomy and stock market are offered by uncertainty (political, economic, social). High uncertainty about the future has several negative effects: it incentivizes companies to postpone investments and hirings, encourages households to cut their expenses, boosts the pressure on the cost of finance (Pastor and Veronesi, 2013), increases the manager risk aversion (Panousi and Papanikolaou, 2012). Friedman (1968), Born and Pfeier (2014), Villaverde et al. (2015) and Bloom (2016) reported a significant connection between economic policy uncertainty and stock market, demonstrating as the former is able to boost the volatility and drop the return of the latter. This pattern, that is shown to behave asymmetrically, is strengthened in some policy-sensitive sectors like defense, health care, finance and infrastructure (Bloom, 2016). An idea to retrieve the degree of national and international uncertainty might arrive from the bond market, which through few fundamental metrics mirrors the general level of insecurity. Some examples are the term spreads (Fama and French, 1989), the long-term government bond performances (Sariannidis et al., 2010) or the credit spreads.

To conclude, some updated studies attempt to focus on more challenging risk factors for modelling return and volatility of the stock market. It is the case of national expenditure in Research and Development (R&D) (Bloom, 2020), media coverage (Tetlock, 2007; Carlin et al., 2014), journalist confidence and press writing clarity (Bloom, 2021), perception of rare disaster (Manela and Moreira, 2017), other than FED monetary policy enforced to the international financial system (Gopinath and Stein, 2018; Maggiori et al., 2020).

Despite the circumstance the vast majority of authors highlighted empirically at least a weak relationship between stock market and some macroeconomic components, anyway, it is important to mention that a minority of literature did not find any support to the causality effect in some markets during particular periods, leaving the debate still vibrant (Chan, Karceski and Lakonishov, 1998; Neifar, 2021).

RETRIEVING THE MACRO-FACTORS

The second chapter of the study is dedicated in attempting to show relationships between most of the macroeconomic variables suggested by previous theory and the Italian Stock Market, in the period between January 2000 and February 2022.

DATA

The coming section aims to define and describe the different variables used in the study. The chosen variables reflect the suggestions coming from the reviewed theory presented in the previous chapter as well as a few others that might have a relevance in the specific framework of the Italian Stock Market.

To conduct the analysis, the collection of data was downloaded from Bloomberg, with the exception of Core Inflation, collected from the official ISTAT website, and of Global and Italian Economic Policy Uncertainty Indices, coming from www.policyuncertainty.com. For all the variables, the closing values have been considered. The dataset is monthly and, as window of research, the period between 31/01/2000 and 28/02/2022 has been considered, that is a total of 266 observations, even if for some components the initial and/or the final dates were not available to date.

The returns and the relative changes considered in the analysis are computed through the logarithm, as following:

$$RC_t = log(V_t) - log(V_{t-1})$$

Where:

V_t = *Variable in t;*

$RC_t = Relative\ change\ of\ V\ from\ (t-1)\ to\ t.$

The composition of the dataset is the following:

CATEGORY	VARIABLE	FIRST DATE	LAST DATE
MARKET	FTSE MIB INDEX	31/01/2000	28/02/2022
COMMODITY	WTI CRUDE OIL	31/01/2000	28/02/2022
	NATURAL GAS	31/01/2000	28/02/2022
GDP	INDUSTRIAL PRODUCTION	31/01/2000	31/01/2022
	UNEMPLOYMENT RATE	31/01/2000	31/01/2022
	R&D AS % OF GDP – SPREAD ITA-OCSE	31/01/2000	31/12/2019
EXPORT	EUR/USD	31/01/2000	28/02/2022
	TRADE BALANCE	31/01/2000	31/01/2022
PURCHASING POWER	CORE INFLATION	31/01/2000	28/02/2022
	REAL INCOME LEVEL	28/02/2005	31/12/2021
US MONETARY POLICY	FED FEDERAL FUNDS TARGET RATE US	31/01/2000	28/02/2022
GOVERNMENT SOLVENCY CONFIDENCE	SPREAD ITA-GER 10Y	31/01/2000	28/02/2022
	DEBT/GDP – SPREAD ITA-GER	30/11/2001	28/02/2022
	TERM SPREAD 10Y-1Y	31/12/2002	28/02/2022
ECONOMIC POLICY UNCERTAINTY	GLOBAL ECONOMIC POLICY UNCERTAINTY	31/01/2000	28/02/2022
	ITALIAN ECONOMIC POLICY UNCERTAINTY	31/01/2000	28/02/2022

R&D % OF GDP – SPREAD ITA-OCSE indicates the spread between Italian Expenditure in R&D as percentual of national GDP and OCSE average Expenditure in R&D as percentual of GDP. Historically, that spread is negative and a tightening or an expansion of the same overtime may transmit an information for the market.
Since data are disclosed annually and in substantial delay, the time series has been monthly adjusted and the last value available is 31/12/2019.

Core Inflation identifies the long run trend in the price level and it is measured by excluding food and energy from classical inflation. The choice of employing the core rather than the classical inflation is generated to avoid excessive problems of interdependence between risk factors, especially with oil and natural gas.

Real Income Level identifies the average Italian Income Level net of full Inflation, giving an estimate of the evolution of the purchasing power for Italians.

Concerning DEBT/GDP RATIO – SPREAD ITA-GER, it measures the spread in percentual points between the level of indebtedness of Italy and Germany, compared to their own national GDP.

About Global Economic Policy Uncertainty Index, it has been constructed and monthly updated by Baker, Bloom and Davis, considering a GDP-weighted average of national Economic Policy Uncertainty indices of 21 countries (accounting for about 71% of global output). Each national index quantifies the newspaper coverage discussing economic policy uncertainty in that month by counting the number of articles containing the words 'Uncertain' or ‘Uncertainty’, ‘Economic’ or ‘Economy’, and one or more policy-relevant terms in national native language. For Italy, the newspapers of reference are Corriere Della Sera and La Stampa.

Since few variables display periodical pattern, in those cases data are seasonally adjusted. It is the instance of Industrial Production, Unemployment, Trade Balance, Core Inflation, but also GDP related measures.

Significant to remark the fact that, being Italy part of the European Union and of the Euro Area, some key procedures are under the control of European supranational entities, such as the monetary and the foreign policy. This could lead to distortions in the way in which the market answers to particular risk factors compared to what observed by previous literature in other geographies (for example Industrial Production, Unemployment or Exchange Rate). For instance, the European Central Bank, in setting its policy, must follow the interests of all members which often are in contrast between themselves, especially when the economies diverge. Furthermore, the same reason justifies the employment of the spread ITA-GER 10Y in the Yield of the Governments Bond and of the spread between Italy and Germany in the level of indebtedness (DEBT/GDP), as Germany represents the risk-free reference country in the Euro area.

At last, to conclude this paragraph regarding data, it is worthy to specify the fact that the proposed macroeconomic risk factors are divided mainly in two categories: traded and not - traded. Between the two types important differences exist and, also if in this text only closing prices at the end of each month have been considered for both, there is to remind that the first ones are continuously available to the public while the second ones not. For this reason, market practitioners respond to traded risk factors instantaneously and relying on certain time-series, while to non-traded variables a continuous value is not available and investors tend to employ expectations to respond to their movements. This means that in some cases data may be distorted by errors of valuation and the understanding of eventual relationships with the market is surely trickier compared to traded factors.

METHODOLOGY

In searching the set of macroeconomic variables able to have an impact on market returns, two primary considerations must be contemplated:

1) It is reasonable to assume that while some variables may have a significant impact on the market at current time, the same could experience scarce or absent ability of suggesting future movements of the market;
2) At the same time, while some regressors may reveal important relations in giving hints on future market movements, the same could be weak in explaining what is driving the market at present time.

Given these premises, it has been decided to adopt two different model specifications for testing macro-factors:

1) An Explanatory specification, taking the form of

$$r_{mkt,t} = b_0 + b_1 * r_{factor,t} + \varepsilon_t;$$

2) A Forecasting specification, through overlapping/aggregate returns, taking the form of

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{factor,t-k--\rightarrow t} + \varepsilon_{t+k},$$

With k indicating the various lengths of overlapping monthly windows examined in this study (k=1, 6, 12, 36, 60).

In this context, statistically significant estimates of the coefficient b_1 indicate reliable relationships between the specific factor and the Italian market.

In a successive moment, to deepen the analysis, the most relevant levers found among the dataset are captured and considered in a set of regressors. Accordingly, two final Arbitrage Pricing Theory (ATP) models will be proposed and backtested:

1) An Explanatory Model, represented as

$$r_{mkt,t} = b_0 + b_1 * r_{factor_1,t} + b_2 * r_{factor_2,t} + \cdots + b_n * r_{factor_n,t} + \varepsilon_t;$$

2) A Forecasting Model, materialized as

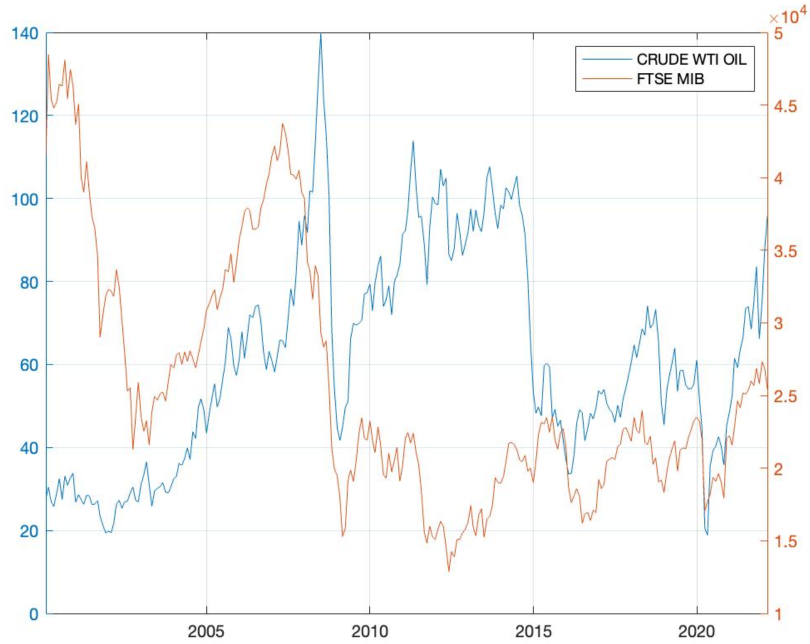
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{factor_1,t-k--\rightarrow t} +$$

$$b_2 * r_{factor_2,t-k--\rightarrow t} + \cdots + b_n * r_{factor_n,t-k--\rightarrow t} + \varepsilon_{t+k}.$$

FACTORS

WTI Crude Oil

Since the mid-1950s, Oil has become the most important source of energy for industrialized countries, permitting the fuel of vehicles and planes throughout the world, the power supply to industry, the household houses heating and the products and chemical fertilizers manufacturing. Oil prices have huge implications for the entire economy.



The WTI Oil price saw its historical peak before of the great recession at 140$ per barrel, while the bottom price was reached on the panic of Covid pandemic, with the entire worldwide economies fixed in their productions and consumptions due to lockdowns.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean OIL	0.0047	0.0134	−0.0108	0.0128
5 Std OIL	0.1136	0.0890	0.0999	0.1518
6 Mean/Std OIL	0.0413	0.1510	−0.1077	0.0845
7 Correlation	0.3723	0.1689	0.3305	0.5681

In general, Oil tends to be a pro-cyclical asset. The correlation coefficient with the FTSE MIB Index is 0.37 for the period 2000-2022, increasing in the last six years at 0.57. The reason beyond this empirical fact may be that the oil consumption is boosted during economic expansions, while is reduced when economies are in difficulty.

Accordingly, a model constructed as

$$r_{mkt,t} = b_0 + b_1 * r_{Oil,t} + \varepsilon_t$$

would likely turn to be spurious, suffering enormously the reverse-causality problem.

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Constant	-0.0028	-0.0035	-0.0023	-6.6824e-04
2 Coefficient	0.2012	0.1007	0.2278	0.2323
3 P-value	3.9015e-10	0.0982	0.0011	1.2959e-07
4 R-2	0.1386	0.0285	0.1092	0.3228

To highlight the trouble, the reverse regression is run:

$$r_{oil,t} = b_0 + b_1 * r_{mkt,t} + \varepsilon_t$$

Even if the coefficient is higher, the results show identical P-value and R-2 for the whole period of analysis, suggesting a bidirectional relationship.

	1 2000-2022
1 Constant	0.0060
2 Coefficient	0.6887
3 P-value	3.9015e-10
4 R-2	0.1386

Anyway, a durable and persisting rise in oil price surely can shrink the demand side of economies and devour business earnings, as also evidenced by theory.

Accordingly, the overlapping return model:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Oil,t-k--\rightarrow t} + \varepsilon_{t+k}$$

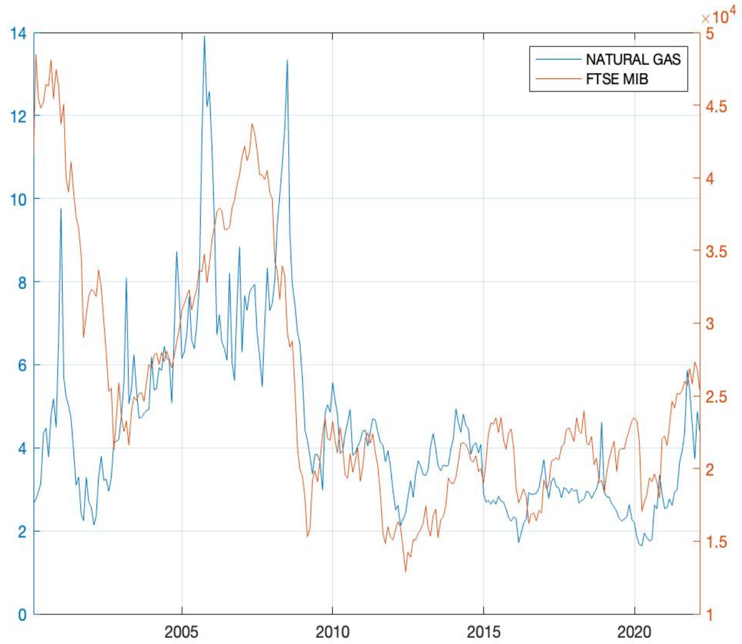
helps in checking the intuition.

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0022	-0.0118	-0.0146	-0.0094	-0.0211	0.0363
2 Coefficient	-0.0026	-0.0720	-0.0735	-0.0712	-0.2034	-0.5214
3 P-value	0.9371	0.0450	0.0909	0.1563	2.6058e-05	1.2068e-24
4 R-2	2.3913e-05	0.0159	0.0119	0.0093	0.0887	0.5214

As expected, the sign of coefficients for each horizon is negative and the magnitude is strengthened with the horizon. The significance of the coefficient and the goodness of fit of the regression follow the same pattern.

Natural Gas

Natural Gas is the principal component in the national production of electricity in Italy, accounting for more than 40% in the last years. Even though previous literature has not documented any empirical fact, in the Italian landscape, Gas may be a significant risk factor in pricing.



Similarly to Oil, the Natural Gas price saw its historical peak before of the great recession and has never recovered a significant quotation in the following years belonging in the period of analysis.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean GAS	0.0019	0.0130	−0.0148	0.0086
5 Std GAS	0.1519	0.1872	0.1197	0.1363
6 Mean/Std GAS	0.0125	0.0693	−0.1234	0.0628
7 Correlation	0.0500	0.0673	0.0770	−0.0104

Differently from oil, Gas is uncorrelated with the Italian stock market. The correlation coefficient is near to zero for the period 2000-2022.

Regressing the market against gas for each time t:

$$r_{mkt,t} = b_0 + b_1 * r_{Gas,t} + \varepsilon_t$$

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Constant	-0.0019	-0.0024	-0.0041	0.0024
2 Coefficient	0.0202	0.0191	0.0443	-0.0047
3 P-value	0.4176	0.5127	0.4607	0.9303
4 R-2	0.0025	0.0045	0.0059	1.0714e-04

Results show no proof of evidence supporting the idea that gas can impact the market.

Anyway, for the same reasons of Oil, to test the effects of a persisting period of high or low returns, the outcomes of the overlapping return model:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Gas,t-k--\rightarrow t} + \varepsilon_{t+k}$$

are highlighted.

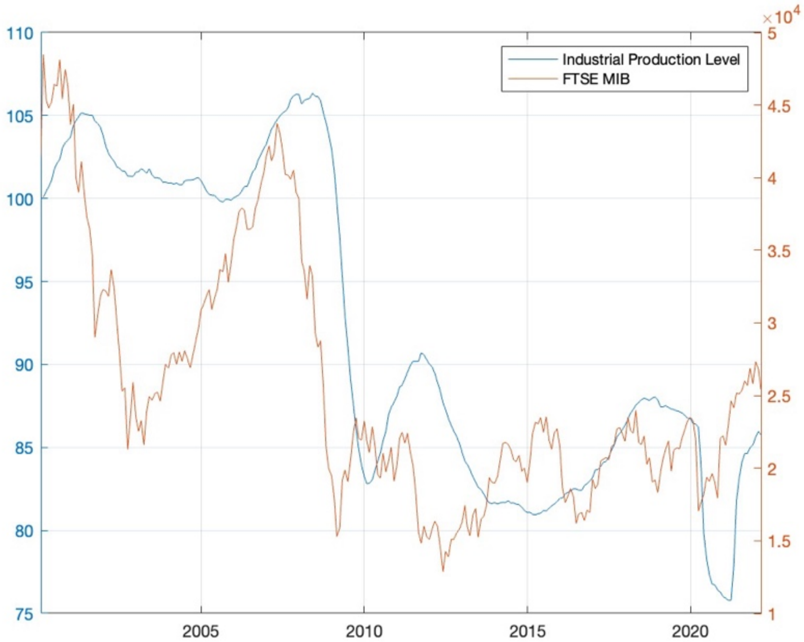
	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0022	-0.0133	-0.0118	-0.0139	-0.0490	-0.2200
2 Coefficient	0.0145	-0.0216	0.1105	0.0401	-0.0351	-0.5348
3 P-value	0.5560	0.4810	0.0024	0.3889	0.4940	1.4069e-34
4 R-2	0.0013	0.0020	0.0380	0.0035	0.0025	0.6519

In this case, no important information is given for small and medium k, but after five years the regression indicates a strong forecasting power for Gas, with an important negative coefficient and a high R-2, as for Oil. Anyway, since there is no a clear pattern when augmenting k, the evidence is not as strong as shown by WTI Crude Oil.

Industrial Production

Industrial Production offers important information about economic output of a country, regardless of its business cycle. Together with agriculture and services, industrial production forms the three major sectors of an economy.

Italy, as well as the major advanced economies in the world, has become a service-oriented country from few decades and the sector has become the largest contributor to GDP. Anyway, although Industrial Production has reduced its contribution to the overall economic product, its significance as a major economic indicator hasn't reduced in the same proportion.



After a good beginning of millennium, Italian industrial production suffered enormously the great crisis, without ever recuperating substantially the pre-levels, and the Covid outbreak in March 2020.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0017	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0269	−0.0409	−0.0695	0.0372
4 Mean IPG	−0.0033	0.0076	−0.0289	0.0153
5 Std IPG	0.0880	0.0313	0.0792	0.1324
6 Mean/Std IPG	−0.0372	0.2424	−0.3650	0.1153
7 Correlation	0.0379	0.0535	−0.0797	0.1221

To notice that the correlation between the two-time series is basically inexistent until the 2016-2022 period, and very weak thereafter. Indeed, observing the image, it is recognizable that the correlation is quite lagged rather than immediate, suggesting the fact the market is able to properly forecast the evolution of the key measure and not at the opposite as hypothesized.

From the model:

$$r_{mkt,t} = b_0 + b_1 * r_{Industrial\_Production,t} + \varepsilon_t,$$

the hint is verified, with low, of different sign and insignificant coefficients.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0016	−0.0029	−0.0068	0.0050
2 Coefficient	0.0265	0.0907	−0.0693	0.0597
3 P–value	0.5395	0.6025	0.4454	0.2690
4 R–2	0.0014	0.0029	0.0063	0.0177

Furthermore, for the same reason, the multi-period return regression

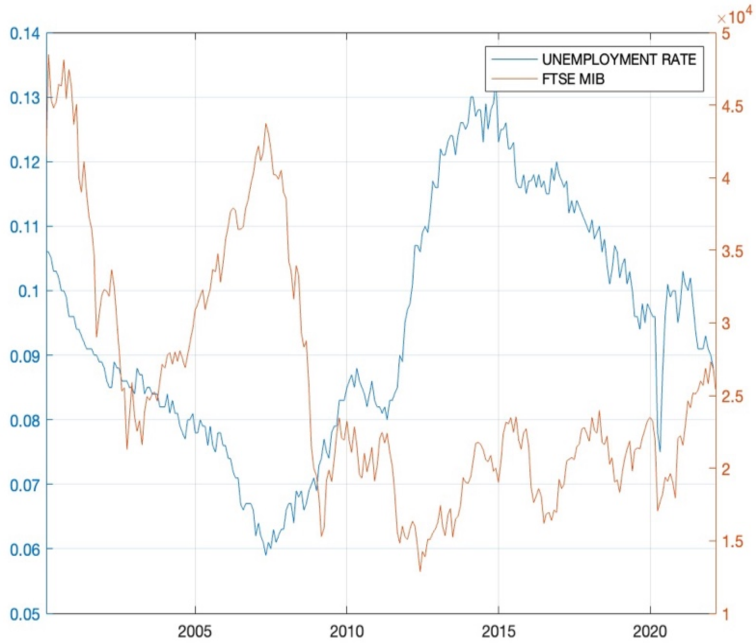
$$r_{mkt,t--\to t+k} = b_0 + b_1 * r_{Industrial\_Production,t-k--\to t} + \varepsilon_{t+k}$$

cannot deliver any meaningful result.

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0022	−0.0159	−0.0337	−0.0131	−0.0538	−0.4430
2 Coefficient	4.9557e–04	−0.0740	−0.1334	0.0142	−0.0190	−0.3410
3 P–value	0.9907	0.0025	1.4365e–08	0.5711	0.5063	2.0738e–24
4 R–2	5.1734e–07	0.0358	0.1261	0.0015	0.0023	0.5178

Unemployment Rate

Unemployment Rate is defined as the percentage of people seeking for a job over the entire labor force. It is considered as a milestone of the performance of a country's labor market. The economic costs of a high unemployment include higher payments from the state for unemployment benefits, reduced personal consumption and production (therefore lower GDP), worse allocation of national recourses and, in general, higher fiscal pressure on companies to finance unemployment welfare.



The Italian Unemployment Rate sharply declined in the first years of 2000s, but due to the 2008 and the sovereign debt crises, its level rose unprecedently. Today, Italian Unemployment is still higher compared to the pre-great recession period.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0017	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0269	−0.0409	−0.0695	0.0372
4 Mean UNEMPLOYMENT GROWTH	−7.0493e−04	−0.0047	0.0059	−0.0039
5 Std UNEMPLOYMENT GROWTH	0.0300	0.0215	0.0273	0.0402
6 Mean/Std UNEMPLOYMENT GROWTH	−0.0235	−0.2195	0.2170	−0.0971
7 Correlation	0.0637	−0.1459	−0.0130	0.2892

Below the output for the model

$$r_{mkt,t} = b_0 + b_1 * r_{unemployment\_Rate,t} + \varepsilon_t:$$

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Constant	-0.0016	-0.0039	-0.0046	0.0048
2 Coefficient	0.1303	-0.3595	-0.0327	0.4472
3 P-value	0.3028	0.1540	0.9012	0.0131
4 R-2	0.0041	0.0213	1.6851e-04	0.0836

From the reading of the statistical table and of the results of the regression, Unemployment Rate appears a tricky factor to fully understand. In particular, the coefficient of the model is substantially negative but weak in significance in the 2000-2007 period, null in the intermediate window and meaningfully positive and significant in the following years. These features are temporarily in line with the change of strategy of the European Central Bank overtime, more and more accommodative in its crisis management. Consequently, at present time, market participants tend to interpret positively an increase of unemployment, in contrast with what happened in the past.

Along the same line of reasoning, modelling returns through the following:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{unemployment\_Rate,t-k--\rightarrow t} + \varepsilon_{t+k},$$

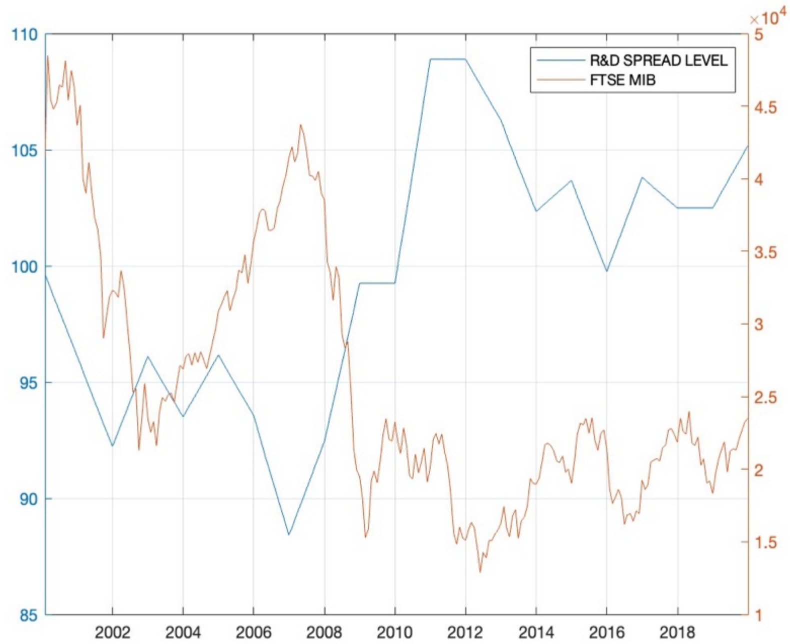
can give back also worthier insights, since the ECB is surely more interested in combatting persistent increasing unemployment rather than momentary one.

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0023	-0.0128	-0.0142	-0.0181	-0.0616	-0.2779
2 Coefficient	-0.1437	0.2387	0.4222	0.3529	0.3992	1.0614
3 P-value	0.2504	0.1123	0.0028	0.0035	2.8456e-04	2.0667e-34
4 R-2	0.0051	0.0100	0.0367	0.0389	0.0668	0.6500

Unsurprisingly, the longer the horizon the greater the coefficient, the significance and the explanatory power.

R&D as Percentage of GDP – Spread ITA-OCSE

Research & Development as Percentage of GDP – Spread ITA-OCSE measures the existing spread between the Italian expenditure and the GDP-weighted average of OCSE expenditure in Research & Development as percentage of their GDP. A drop in the time series implies a recovery of Italy, whereas an expansion translates into a worsening of the current level of difference.



Traditionally, Italy spends less than advanced economies in R&D and this trend has accentuated in the window of analysis, especially after the 2008 recession.

	1 2000–2019	2 2000–2007	3 2008–2015	4 2016–2019
1 Mean FTSE MIB	−0.0024	−0.0022	−0.0048	0.0019
2 Std MIB	0.0597	0.0531	0.0689	0.0538
3 Mean/Std FTSE MIB	−0.0397	−0.0409	−0.0695	0.0360
4 Mean R&D change	2.3069e−04	−6.4837e−04	6.9109e−04	0.0011
5 Std R&D change	0.0033	0.0033	0.0038	0.0018
6 Mean/Std R&D change	0.0689	−0.1955	0.1824	0.6313
7 Correlation	−0.1578	−0.1458	−0.2079	−0.0132

As suggested by Bloom (2020), also for Italy a relation between the measure and the stock market appears in existence. The correlation coefficient is negative and rather weak at -0.16, even though it disappears in the last available timeframe between 2016-2019. Similar results are delivered by the regression:

$$r_{mkt,t} = b_0 + b_1 * r_{R\&D\_Spread\_ITA\_OCSE,t} + \varepsilon_t$$

	1 2000–2019	2 2000–2007	3 2008–2015	4 2016–2019
1 Constant	−0.0017	−0.0037	−0.0022	0.0024
2 Coefficient	−2.8159	−2.3351	−3.7782	−0.4072
3 P−value	0.0146	0.1541	0.0443	0.9288
4 R−2	0.0249	0.0213	0.0432	1.7534e−04

In particular, all coefficients are negative and, in the last interval, the coefficient weakens and do not exhibit any statistical significance. The same pattern is observable in the R-2s.

Deepening the analysis, from the modelling through overlapping returns,

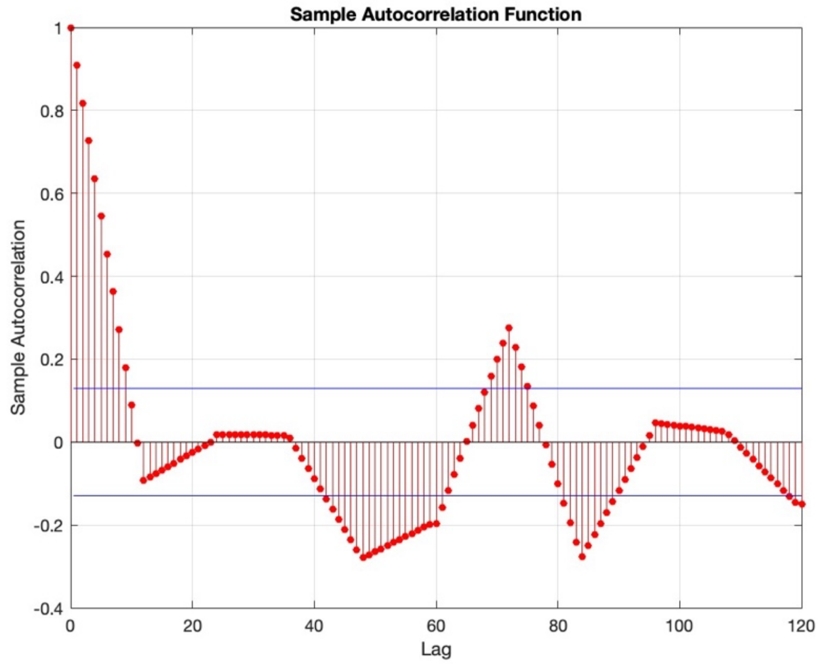
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{R\&D\_Spread\_ITA\_OCSE,t-k--\rightarrow t} + \varepsilon_{t+k}$$

it is possible to understand more.

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0039	−0.0234	−0.0282	−0.0314	−0.0774	−0.2405
2 Coefficient	−2.2430	−1.4416	−1.4029	0.5135	0.8201	2.5511
3 P−value	0.0598	0.0163	0.0047	0.2720	0.0492	8.5430e−10
4 R−2	0.0176	0.0293	0.0416	0.0068	0.0232	0.2350

The coefficients remain negative for timeframes until one year, suggesting that a fall in R&D relative expenditure in the past year impacts negatively the returns for the next one. Anyway, for long horizons, the values are curiously positive. A possible explanation for this pattern is the cyclical nature of the factor, whereby particularly prolonged periods of growth may trigger overtime an inversion of trend, causing new investments, a recovery in the spread and, consequently, positive energy for the stock market.

The presence of cyclicality can be detected by observing the ACF (Autocorrelation Function) of the time series.



Exchange Rate EUR/USD

EUR/USD is considered the most important exchange rate worldwide, including the two major currencies in the world. For Italy, the pair can be used as proxy for the entire exchange rate, since the most of Italian import and export occurs through those.

The Euro gained more than 50% over the Dollar during the first decade of 2000 but in the aftermath, the European currency crashed in the burden of ECB of rescuing Euro and economies in difficulty after the two crises.

Below the statistical table comparing the Italian Stock Market with EUR/USD.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean EUR/USD	5.4627e−04	0.0046	−0.0036	4.3700e−04
5 Std EUR/USD	0.0277	0.0258	0.0344	0.0183
6 Mean/Std EUR/USD	0.0198	0.1786	−0.1033	0.0239
7 Correlation	0.1935	−0.1275	0.3950	0.1862

About the model $r_{mkt,t} = b_0 + b_1 * r_{EUR\_USD} + \varepsilon_t$,

the coefficients coming from the different sub-windows are intricate:

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0021	−9.6235e−04	−0.0020	0.0020
2 Coefficient	0.4297	−0.2624	0.7895	0.6327
3 P−value	0.0015	0.2132	8.1489e−05	0.1122
4 R−2	0.0375	0.0163	0.1560	0.0347

Considering the entire period of analysis, as well as in the last two stages, the coefficient is positive and highly significant, but looking only at 2000-2007, the same is negative. A possible reason for the pattern is the switch of Italy as debtor from very safe (2007 Fitch rating AA-) to partly risky (2022 Fitch rating BBB). Indeed, if until the great recession the market was more interested in EUR/USD as lever of Italian competitiveness as exporter, thereafter the rate may have become a representation of the economic health of weak Euro countries.

Over the ability of the exchange rate to explain present market returns, it is interesting to observe also whether exists a predictive power, through:

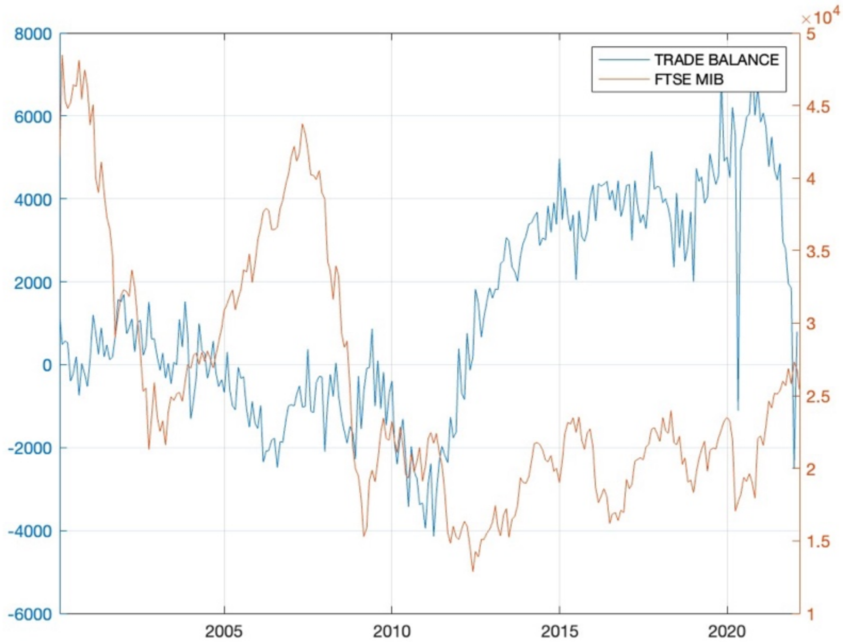
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{EUR\_USD,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0022	-0.0123	-0.0141	-0.0170	-0.0411	-0.0173
2 Coefficient	0.0645	-0.1736	-0.1212	0.0542	-0.1564	-1.7599
3 P-value	0.6343	0.2305	0.4244	0.7257	0.3218	2.7557e-41
4 R-2	8.6832e-04	0.0057	0.0027	5.7388e-04	0.0051	0.7193

From the visualization of results, evidence of the existence of the model is present only for long lasting exchange rates movements (i.e., k=60 months). In that case, R-2 is very high (0.72), and the coefficient is deeply negative, signaling an inverse relation between the two variables. The finding suggests that long exchange movements can seriously slice or strengthen Italian corporate profits in the contemporaneous global economy.

Trade Balance

Trade Balance measures the difference between the import and the export of a country in currency terms. It is said to be in surplus if the difference is positive and in deficit otherwise. The Balance of Trade is considered an important macro-factor since is either able to influence national growth and corporate cash-flows.



During the entire first decade of 2000s, the Italian Trade Balance has been around the parity, whereas in the second one the value of export dragged the national economic recovery, considerably exceeding import. Anyway, from 2021 the Balance is heavily suffering the massive price increment of commodities.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0031
2 Std MIB	0.0614	0.0531	0.0689	0.0622
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0495
4 Mean TRADE BALANCE change	−1.7008e−04	−0.0015	0.0049	−0.0048
5 Std TRADE BALANCE change	0.1031	0.0677	0.0838	0.1537
6 Mean/Std TRADE BALANCE change	−0.0016	−0.0226	0.0581	−0.0315
7 Correlation	0.0304	−0.1330	0.1667	0.0148

To investigate the contemporaneous relation between the Italian Trade Balance and the FTSE MIB Index, it is possible to explore the information of the statistics table and of the results from the regression:

$$r_{mkt,t} = b_0 + b_1 * r_{Trade\_Balance,t} + \varepsilon_t.$$

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0016	−0.0023	−0.0055	0.0031
2 Coefficient	0.0181	−0.1043	0.1370	0.0060
3 P−value	0.6232	0.1942	0.1084	0.9013
4 R−2	9.2261e−04	0.0177	0.0278	2.1828e−04

The coefficient of the regression for the entire period of analysis, as well as the correlation coefficient, is basically null and not significant. In addition, it is dependent on the sub-period for what concerns sign and magnitude, giving a hint of model rejection.

At the opposite, aggregate past changes of Trade Balance appear to experience remarkable forecasting ability:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Trade\_\text{Balance},t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0044	−0.0273	−0.0362	−0.0450	−0.0911	−0.2297
2 Coefficient	−0.0199	0.1657	0.1627	0.3990	0.3826	0.7684
3 P−value	0.7283	0.1329	0.1779	7.6171e−04	5.2154e−04	7.8288e−13
4 R−2	6.0477e−04	0.0115	0.0096	0.0622	0.0706	0.3060

The evidence is particularly true for longer horizons, since this ability augments with time. Unsurprisingly, the coefficients are greater than 0 for all significant ones, signaling a positive relation between past improvements in the Italian Balance of Trade and national market returns.

Core Inflation

Core Inflation identifies the long run trend in the price level by excluding food and energy from inflation, making classical inflation much less volatile. The employment of Core rather than classical, in addition, permits to avoid excessive problems of interdependence with other risk factors, mainly with Oil and Gas. For the purposes of this study, the time series employed in this paragraph is not pure Core Inflation, but the relative change of it, so to understand whether an acceleration or a braking can impact the market.

Italian Core Inflation has been in a downward trend from 2000 and from few years is stable very low between 0.50% and 1.00%. Remarkably, Core Inflation do not show an extraordinary surge at the beginning of 2022 as ordinary Inflation, since the price boosting has been due principally to the commodity skyrocketing, which is slow to be transmitted to real economy.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean INFLATION	−0.0031	−0.0011	−0.0135	0.0074
5 Std INFLATION	0.2626	0.0705	0.1764	0.4505
6 Mean/Std INFLATION	−0.0117	−0.0150	−0.0763	0.0165
7 Correlation	0.0437	0.0759	0.0501	0.0470

About statistics, for every window, Core Inflation has displayed means of the same signs of the Italian market and the correlation has remained steady around 5%, indicating a weak but positive correlation in the two series of data.

Seeking to model market returns through current Core Inflation evolution, that is

$$r_{mkt,t} = b_0 + b_1 * r_{Core\_Inflation,t} + \varepsilon_t,$$

the obtained results are the following:

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0018	−0.0021	−0.0045	0.0023
2 Coefficient	0.0102	0.0572	0.0196	0.0065
3 P–value	0.4788	0.4602	0.6312	0.6907
4 R–2	0.0019	0.0058	0.0025	0.0022

The table do not exhibit proof of evidence for Core Inflation as significant risk factor for the FTSE MIB. Anyway, if monthly accelerations or slowdowns in Core Inflation do not worry market participants, persisting and long movements should be considered. From overlapping returns model:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Core\_Inflation,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0021	-0.0167	-0.0277	-0.0124	-0.0462	-0.2617
2 Coefficient	0.0219	-0.0865	-0.1562	0.0210	0.0042	-0.2763
3 P-value	0.1239	5.2312e-04	9.8829e-06	0.6663	0.9436	1.3515e-04
4 R-2	0.0090	0.0469	0.0786	8.6649e-04	2.6303e-05	0.0972

The regression evidences negative and significant coefficients for 6 to 12 and for long (k=60) aggregate relative Core Inflation changes, establishing a substantial inverse relation between the two variables.

Real Income Level

Real Income Level identifies the average Italian Income Level evolution net of the overall increase in cost of living, measured by Inflation. It gives an estimate of the evolution of purchasing power for national population, who through household consumption shapes corporate cash-flows.

Italian Real Income Level has only marginally grown during the 2005-2021 timeframe by about 0.35%. In addition to the general low pace of the Italian income growth, the two inflation bursts observed in Italy since 2011 and since 2021 have eaten up most of the weak nominal income increment.

	1 2005-2021	2 2005-2007	3 2008-2015	4 2016-2021
1 Mean FTSE MIB	-0.0012	0.0061	-0.0075	0.0051
2 Std MIB	0.0616	0.0286	0.0697	0.0602
3 Mean/Std FTSE MIB	-0.0192	0.2140	-0.1079	0.0844
4 Mean INCOME GROWTH	1.6735e-04	4.0292e-04	2.0024e-04	1.4602e-05
5 Std INCOME GROWTH	0.0020	0.0018	0.0024	0.0015
6 Mean/Std INCOME GROWTH	0.0826	0.2215	0.0827	0.0100
7 Correlation	0.0389	-0.1947	-0.0107	-0.1120

The market reactivity to contemporaneous changes in Real Income Level can be inspected by means of correlation and regression coefficients. From the examination of the former, the factor seems not to influence present market changes, presenting very low values for all windows. Similar results are obtained by examining the regression:

$$r_{mkt,t} = b_0 + b_1 * r_{Real\_Income\ \_Level,t} + \varepsilon_t$$

	1 2005-2021	2 2005-2007	3 2008-2015	4 2016-2021
1 Constant	-0.0011	0.0014	-0.0053	0.0035
2 Coefficient	2.3513	0.8246	5.2315	-4.4402
3 P-value	0.2720	0.7352	0.1020	0.3878
4 R-2	0.0060	0.0033	0.0288	0.0107

As a matter of fact, the sensitivities appear far to be statistically significant and the R-2 tends to zero for each sub-period. Anyway, it is reasonable to think that increases in the purchasing power are slow to manifest effects. From a macroeconomy point of view, a possible real wage enhancement or weakening needs time to involve capital markets investment, primarily because agents must be able to feel a true increase in their spending and saving ability.

To empirically test the reasoning, the following model is proposed:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Real\_Income\_Level,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0040	-0.0287	-0.0543	-0.0893	-0.1360	-0.1085
2 Coefficient	-2.1881	2.7059	8.1754	12.1568	9.5585	-3.7141
3 P-value	0.3012	0.2273	6.3440e-05	2.5656e-12	8.2970e-09	0.1050
4 R-2	0.0053	0.0075	0.0814	0.2424	0.1828	0.0185

In this case, the Real Income Level growth shows ability in positively influencing the market for intermediate expirations (from 12 to 36 months), whereas for short or long terms there is no substantial evidence because the coefficients are rejected.

FED Federal Funds Target Rate US

The Federal Funds Rate is the interest rate at which USD banks and credit institutions lend and borrow uncollateralized liquidity between themselves in the overnight market. The FED intervenes in the market to follow its target rate decision, influencing the money supply and, therefore, the economy in the United States.

From the beginning of 2000, FED employed the Target Rate to offset the consequences of the three US recessions, which are the 2001 dotcom bust, the 2008 financial crisis and the 2020 pandemic outbreak.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean FED change	−0.0117	−0.0062	−0.0191	−0.0094
5 Std FED change	0.1727	0.0857	0.1780	0.2404
6 Mean/Std FED change	−0.0675	−0.0729	−0.1071	−0.0390
7 Correlation	0.2613	0.1310	0.1052	0.5065

Since FED decisions are strongly influenced by the American business cycle, that in turn is considerably interconnected with the European and the Italian cycles, the Target Rate shows a cyclical behavior with respect to the Italian Stock Market, falling during market turmoil and boosting in expansion.

For the same reason, the results of the model:

$$r_{mkt,t} = b_0 + b_1 * r_{FED\_Target\_Rate,t} + \varepsilon_t,$$

cannot be accepted. At the opposite, from the image, it is clear that an inverse modelling would be surely more appropriate:

$$r_{FED\_Target\_Rate,t} = b_0 + b_1 * r_{mkt,t} + \varepsilon_t.$$

Below the statistics from the two different specifications, confirming an inverse or bidirectional causality effect:

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−7.6372e−04	−0.0017	−0.0040	0.0035
2 Coefficient	0.0929	0.0812	0.0407	0.1308
3 P−value	1.6463e−05	0.2010	0.3129	4.1439e−06
4 R−2	0.0683	0.0172	0.0111	0.2565

	1 2000–2022
1 Constant	−0.0103
2 Coefficient	0.7351
3 P-value	1.6463e−05
4 R-2	0.0683

In order to comprehend if FED policy is able to really effect the Italian market, a long-term analysis is more appropriate. From the overlapping return model:

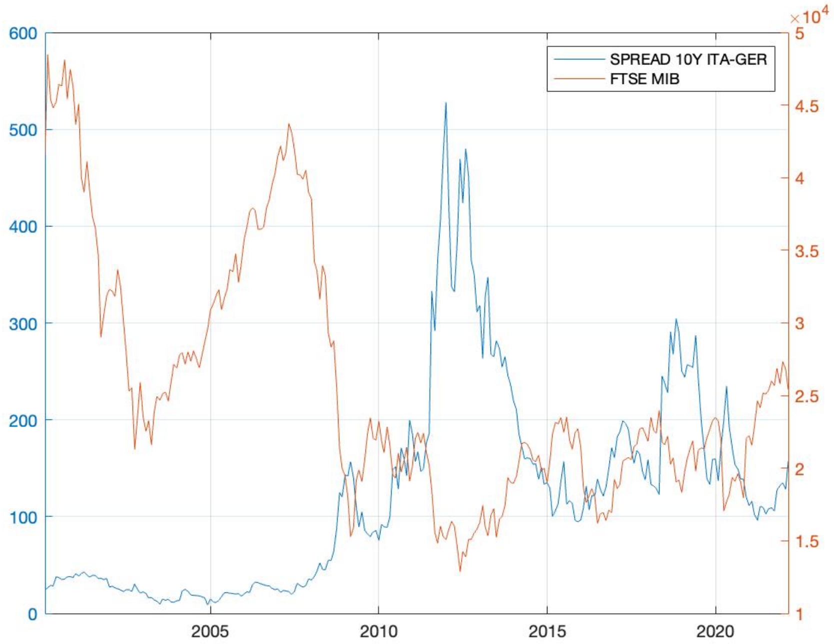
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{FED\_Target\_Rate,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0041	−0.0235	−0.0206	−0.0261	−0.0979	−0.2855
2 Coefficient	0.0285	0.0254	0.0741	0.0030	−0.0672	−0.1635
3 P-value	0.3600	0.3521	0.0019	0.8865	4.8392e−04	6.7085e−13
4 R-2	0.0042	0.0044	0.0497	1.1551e−04	0.0713	0.3075

At this stage, previous theory indications emerge vigorously (Gopinath and Stein, 2018; Maggiori et al., 2020). Empirically, American monetary policy appears a long-run risk factor for the FTSE MIB Index, presenting as expected a negative coefficient (-0.16) and assuming maximum significance (p-value about 0) and R-2 (0.31) for the longest window.

Spread ITA-GER 10Y

The Spread ITA-GER 10Y indicates the difference in basis points between the Italian 10-years government bond and the equivalent issued by the German government. Because the Germany Bund is considered the haven asset in the Eurozone, the spread value represents the credit risk for Italy.



About the evolution, the Spread fluctuated within few basis points until the great crisis, between 0.10% and 0.40%. With the explosion of the financial crisis and, above all, of the sovereign debt crisis, the factor has become a leading component in the investment decision of market participants.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean SPREAD	0.0071	0.0061	0.0084	0.0066
5 Std SPREAD	0.1539	0.1611	0.1583	0.1400
6 Mean/Std SPREAD	0.0459	0.0380	0.0533	0.0469
7 Correlation	−0.4698	−0.2308	−0.6717	−0.4743

The correlation analysis with the Italian stock market confirms what said. For all sub-periods the coefficients are negative, weaker for the period until the crisis, highest during the debt crisis and more relaxed thereafter. To reach the same conclusions through econometric techniques, the following specification is presented:

$$r_{mkt,t} = b_0 + b_1 * r_{Spread\_ITA-GER\ 10Y,t} + \varepsilon_t$$

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Constant	-5.2197e-04	-0.0017	-0.0023	0.0037
2 Coefficient	-0.1874	-0.0761	-0.2921	-0.2104
3 P-value	5.9477e-16	0.0229	1.2609e-13	1.9639e-05
4 R-2	0.2207	0.0533	0.4512	0.2250

The regression evidences the yet mentioned conclusions over different periods in terms of strength, significance, and explanatory ability. Through overlapping return model, it is possible to visualize an eventual predictive power of the Spread:

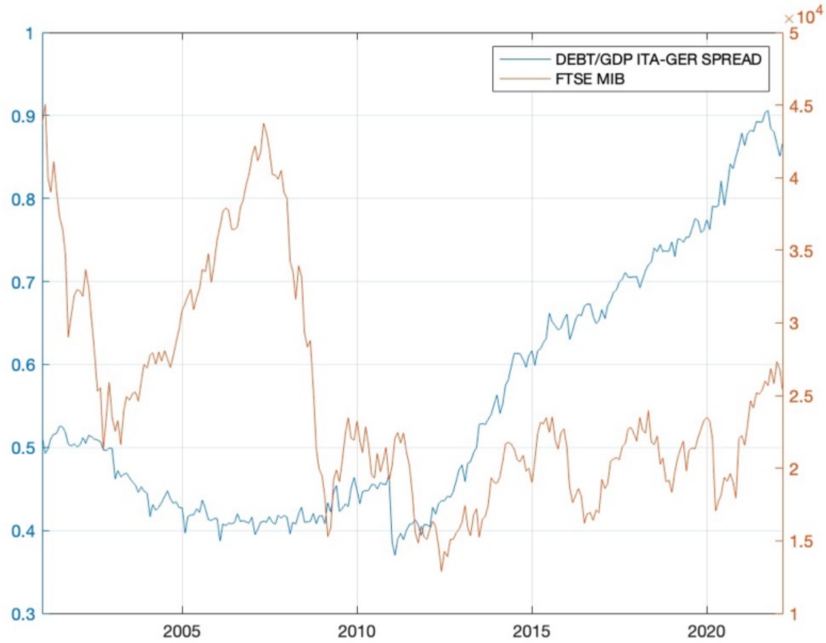
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Spread\_ITA\_GER\_10Y,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	-0.0021	-0.0129	-0.0136	-0.0049	-0.0166	-0.2618
2 Coefficient	-0.0234	-0.0121	-0.0272	-0.0548	-0.0960	0.1412
3 P-value	0.3383	0.6504	0.3414	0.0481	1.9144e-04	1.2391e-06
4 R-2	0.0035	8.1975e-04	0.0038	0.0180	0.0704	0.1521

Interpreting the outcome, Spread shows negative but notable weaker coefficients compared to the previous model for small and medium expirations. The best statistical results are for the 36 months window. Counterintuitively, the coefficient is positive (0.14) for long horizons (k=60). This may be explained by the recurring nature of business cycle, for which crises and expansions follow a regular pattern in the long run.

Debt/GDP – Spread ITA-GER

In terms of government solvency and stability, the outstanding amount of national public debt as portion of Gross Domestic Product is a relevant ingredient. For the purposes of this research, because of the ratio debt to GDP is not able to give any information in itself without taking into account geography and historical period, it has been considered the spread in percentual points between the Italian and the German pending government debt as share of national product.



Interestingly, the differential remained among the band 40% and 50% until the escalation of the sovereign debt crisis, when the Italian debt started a protracted period of raising.

	1 2001–2022	2 2001–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0021	−0.0031	−0.0048	0.0023
2 Std MIB	0.0614	0.0520	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0347	−0.0587	−0.0695	0.0372
4 Mean DEBT/GDP ITA–GER SPREAD change	0.0021	−0.0026	0.0051	0.0037
5 Std DEBT/GDP ITA–GER SPREAD change	0.0258	0.0241	0.0322	0.0162
6 Mean/Std DEBT/GDP ITA–GER SPREAD change	0.0796	−0.1096	0.1574	0.2263
7 Correlation	−0.0247	0.1277	−0.1274	0.0358

Considering quite straightforward that additional government debt will not create immediate effect in the economy, either the statistical table or the specification

$$r_{mkt,t} = b_0 + b_1 * r_{DEBT/GDP\_Spread\_ITA\_GER,t} + \varepsilon_t$$

show any clue about a possible contemporaneous causality effect between the FTSE MIB and the examined spread.

	1 2001–2022	2 2001–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0020	−0.0023	−0.0034	0.0018
2 Coefficient	−0.0590	0.2755	−0.2720	0.1372
3 P–value	0.6947	0.2414	0.2213	0.7623
4 R–2	6.1218e−04	0.0163	0.0162	0.0013

From this point of view, the modelling through overlapping returns is surely more appropriate:

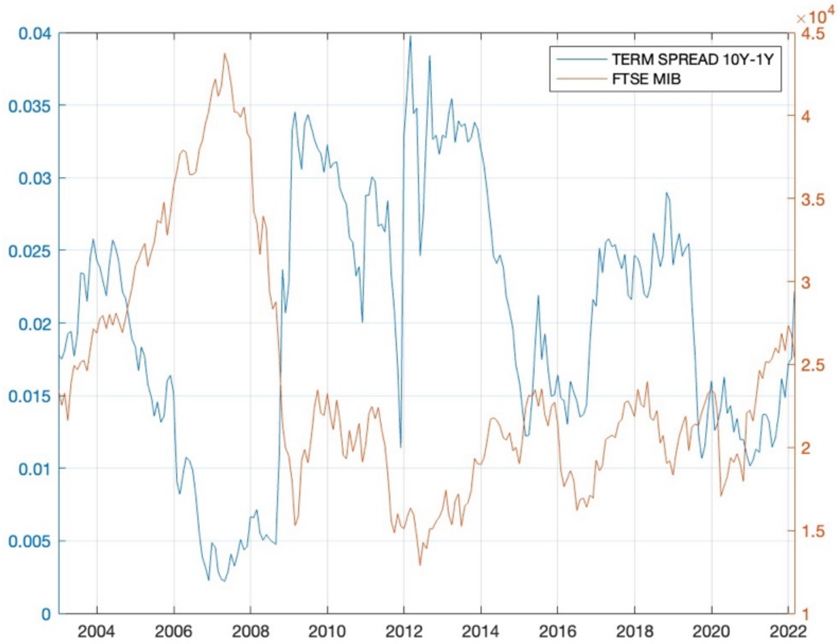
$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{DEBT/GDP\_Spread\_ITA\_GER,t-k--\rightarrow t} + \varepsilon_{t+k}$$

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0045	−0.0289	−0.0407	−0.0346	−0.0688	−0.2894
2 Coefficient	0.0629	0.3514	0.4498	0.1983	0.0628	1.2136
3 P–value	0.6866	0.1012	0.0386	0.2713	0.6911	1.1260e−19
4 R–2	8.1541e−04	0.0137	0.0224	0.0068	9.5933e−04	0.4436

Unexpectedly, the Italian stock market seems not to interpret as harmful a relative increment of Italian government debt, despite the non-excellent financial situation of the country. Indeed, the coefficient stands positive for each overlapping window k, even if maximum significance and relevant forecasting power is exhibited only for 5 years. A potential economic justification is the strong ability of spending which European governments own, able to have heavy repercussions in corporate counts.

Term Spread 10Y-1Y

Term Spread, or slope of the yield curve, indicates the difference between a long-term and a short-term interest rate for the same issuer. A substantial negative relationship with future economic activity, in delay of about four to six quarters, has been demonstrated in the United States (Estrella, 2005). In this study, the spread between the yields of the Italian government bond at 10 years and 1 year has been explored.



In the past twenty years, it is noteworthy how the term spread has forecasted the great crisis in 2008, being at its minimal values from the end of 2006. This is at least partly true also for the sovereign debt crisis and the pandemic crisis.

Although theory has advised for a brilliant forecasting rather than explanatory ability for the Term Spread, it is anyway possible to investigate how it co-moves with the Italian stock market:

	1 2003-2022	2 2003-2007	3 2008-2015	4 2016-2022
1 Mean FTSE MIB	3.3928e-04	0.0058	-0.0048	0.0023
2 Std MIB	0.0592	0.0355	0.0689	0.0621
3 Mean/Std FTSE MIB	0.0057	0.1621	-0.0695	0.0372
4 Mean TERM-SPREAD	9.4869e-04	-0.0147	0.0088	0.0041
5 Std TERM-SPREAD	0.1764	0.1971	0.2006	0.1164
6 Mean/Std TERM-SPREAD	0.0054	-0.0747	0.0440	0.0350
7 Correlation	-0.1020	-0.0657	-0.1459	-0.0379

And from the specification

$$r_{mkt,t} = b_0 + b_1 * r_{Term\_Spread\_10Y\_1Y,t} + \varepsilon_t:$$

	1 2003–2022	2 2005–2007	3 2008–2015	4 2016–2022
1 Constant	3.7179e–04	0.0056	–0.0043	0.0024
2 Coefficient	–0.0343	–0.0118	–0.0501	–0.0202
3 P–value	0.1229	0.6120	0.1605	0.7483
4 R–2	0.0104	0.0043	0.0213	0.0014

The correlation for 2003-2022 exhibits a weak but constant tendence of co-movement between the two variables (-0.10), slightly accentuated in the intermediate window (-0.15). The results of the previous model specification confirm the same pattern of sign and strength, but b_1 presents no significance at all levels, warning that not enough evidence exists for a possible effect of the Term Spread over the market.

To prove what suggested by theory in other markets, the overlapping return model is certainly more suitable:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Term\_Spread\_10Y\_1Y,t-k--\rightarrow t} + \varepsilon_{t+k}$$

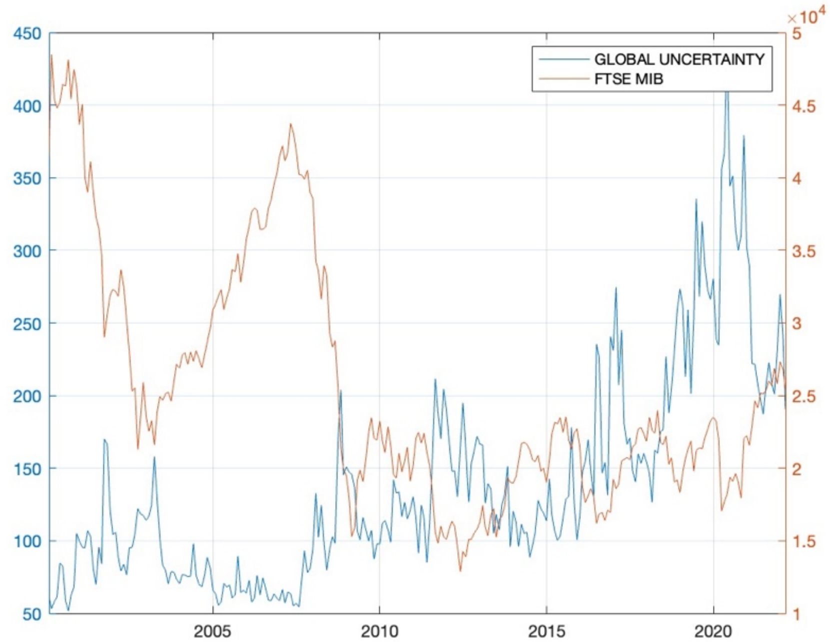
	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	–0.0044	–0.0252	–0.0321	–0.0272	–0.0567	–0.1338
2 Coefficient	–0.0071	0.0208	0.0133	–0.2225	–0.2626	–0.0599
3 P–value	0.7622	0.4374	0.6258	1.6354e–23	6.3635e–36	0.1106
4 R–2	4.5890e–04	0.0031	0.0013	0.4320	0.6139	0.0180

The regression proves the figures of Estrella (2005), with a significant postponed inverse relationship between Term Spread and FTSE MIB. The effect, for Italy, is outstanding in the medium run, whereas poor in the long and absent until 12 months.

Global Economic Policy Uncertainty

The Global Economic Policy Uncertainty Index is composed by Baker, Bloom and Davis. It reflects a GDP-weighted average of national Economic Policy Uncertainty indices of 21 countries, which count for about 71% of global GDP. Each national index quantifies the newspaper coverage discussing economic policy uncertainty in that month.

Elevated economic policy uncertainty about the future has several negative effects for companies, including the postponement of investments and hirings and household expenses remodulation.



From 2000 to today, the Global Economic Policy Index has notably soared in occasion of the four European crises, as well as after the 2016 Trump election and the successive inception of the US-China Trade War.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean GLOBAL UNCERTAINTY change	0.0042	0.0052	0.0014	0.0066
5 Std GLOBAL UNCERTAINTY change	0.1784	0.1752	0.1771	0.1865
6 Mean/Std GLOBAL UNCERTAINTY change	0.0238	0.0297	0.0081	0.0352
7 Correlation	−0.3046	−0.3349	−0.3265	−0.2520

Unsurprisingly, the Index is inversely correlated with the Italian stock market. As a matter of fact, the correlation is negatively weak but not negligible for all sub-periods (-0.30 for the entire period). The ability of the Global Economic Policy Index in explaining the market movements can be tested through the following:

$$r_{mkt,t} = b_0 + b_1 * r_{Global\_Economic\_Policy\_Uncertainty,t} + \varepsilon_t$$

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0014	−0.0016	−0.0046	0.0029
2 Coefficient	−0.1048	−0.1015	−0.1269	−0.0839
3 P–value	4.2694e−07	7.9798e−04	0.0013	0.0303
4 R–2	0.0928	0.1122	0.1066	0.0635

Despite the fact the explanatory power is not particularly high (0.09), the factor presents all the features to be considered. Indeed, the coefficient is negative (-0.10), significant and constant during the whole period of analysis. To verify whether a change in the Global Economic Policy Index can offer any signal for future returns of the Italian market index, it is possible to inspect the results of the coming regression:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{Global\_Economic\_Policy\_Uncertainty,t-k--\rightarrow t} + \varepsilon_{t+k}$$

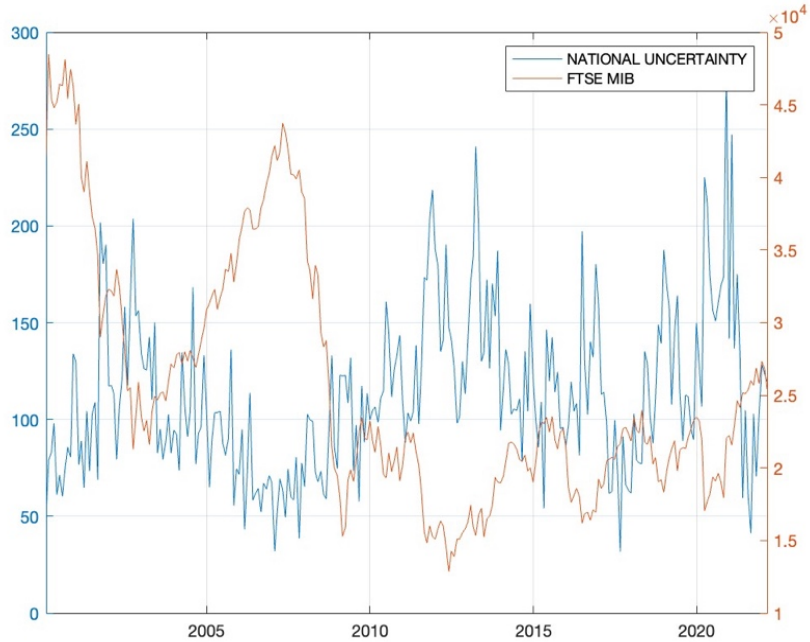
	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0045	−0.0244	−0.0224	−0.0293	−0.0743	−0.2517
2 Coefficient	0.0170	−0.0316	−0.1757	0.0334	0.1203	0.5747
3 P–value	0.4652	0.4354	4.5520e−04	0.5763	0.0620	2.7619e−17
4 R–2	0.0027	0.0031	0.0631	0.0018	0.0210	0.3988

Evidence for the existence of the regression is produced only for 12 and 60-months overlapping windows. For the former, the coefficient shows an expected negative sign, while for the latter, b_1 is positive and the R-2 is considerable. As for the Spread ITA-GER 10Y, the indication might be described by the recurring nature of business cycle, for which crises and expansions follow a regular pattern over long periods.

National Economic Policy Uncertainty

The National Economic Policy Uncertainty Index, as for the Global one, is constituted by Baker, Bloom and Davis. For Italy, the Index quantifies the newspaper coverage of 'Corriere Della Sera' and 'La Stampa' discussing economic policy uncertainty in a specific month. Since the correlation with the Global Economic Policy Uncertainty Index is only modest, even this additional factor is covered.

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Correlation	0.3205	0.4178	0.1420	0.3752



From 2000 to today, the Global Economic Policy Index has notably soared in occasion of the four European crises, as well as after the 2016 Trump election and the successive inception of the US-China Trade War.

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Mean FTSE MIB	−0.0018	−0.0022	−0.0048	0.0023
2 Std MIB	0.0614	0.0531	0.0689	0.0621
3 Mean/Std FTSE MIB	−0.0301	−0.0409	−0.0695	0.0372
4 Mean NATIONAL UNCERTAINTY change	0.0033	0.0070	−0.0015	0.0044
5 Std NATIONAL UNCERTAINTY change	0.3361	0.3524	0.2824	0.3791
6 Mean/Std NATIONAL UNCERTAINTY change	0.0097	0.0199	−0.0053	0.0115
7 Correlation	−0.1636	−0.1448	−0.1075	−0.2552

Also in this case, the Index is inversely correlated with the FTSE MIB but, interestingly, the correlation coefficient is less marked compared with that of the Global Index. The power of the Italian Economic Policy Index in explaining the market movements can be tested through the following model:

$$r_{mkt,t} = b_0 + b_1 * r_{National\_Economic\_Policy\_Uncertainty,t} + \varepsilon_t$$

	1 2000–2022	2 2000–2007	3 2008–2015	4 2016–2022
1 Constant	−0.0017	−0.0020	−0.0048	0.0025
2 Coefficient	−0.0299	−0.0218	−0.0262	−0.0418
3 P–value	0.0076	0.1570	0.3023	0.0282
4 R–2	0.0268	0.0210	0.0116	0.0651

On the same wavelength, the coefficient is marginally negative (-0.03). In addition, the regression is able to explain only a minimal part the market variability (R-Squared = 0.027), confirming the clue that the International Economic Policy Uncertainty is able to impact in a greater way the Italian equity.

Regarding the overlapping returns model

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{National\_Economic\_Policy\_Uncertainty,t-k--\rightarrow t} + \varepsilon_{t+k},$$

the conclusions are the same of those observed for the global case.

	1 k=1	2 k=6	3 k=12	4 k=24	5 k=36	6 k=60
1 Constant	−0.0044	−0.0260	−0.0301	−0.0301	−0.0683	−0.1870
2 Coefficient	−0.0147	0.0336	−0.0826	0.1355	0.2468	0.4997
3 P–value	0.2727	0.2708	0.0563	0.0093	5.7500e−06	3.3721e−19
4 R–2	0.0060	0.0062	0.0191	0.0376	0.1175	0.4349

IDENTIFYING THE MODELS

After having analyzed the most important levers suggested by previous theory in a univariate mode in the Italian market, this chapter is focused on the application of the major findings coming from the previous chapter. In this way, the Italian FTSE MIB Index is modelled by means of two different parametrizations:

1) An Explanatory Multifactor Model, able to explicate the reasons for which the market is moving at present time, parametrized as:

$$r_{mkt,t} = b_0 + b_1 * r_{factor_1,t} + b_2 * r_{factor_2,t} + \cdots + b_n * r_{factor_n,t};$$

2) A Forecasting Multifactor Model, able to give insights about future market returns, parametrized as:

$$r_{mkt,t--\rightarrow t+k} = b_0 + b_1 * r_{factor_1,t-k--\rightarrow t} +$$

$$b_2 * r_{factor_2,t-k--\rightarrow t} + \cdots + b_n * r_{factor_n,t-k--\rightarrow t}.$$

EXPLANATORY MODEL

The construction of an Explanatory Multifactor Model responds to the commitment of explaining why the Italian stock market is moving at current time.

From the univariate analyses conducted on single factors in the previous chapter, the factors indicated to have the most significative impact on present market returns are the following:

	FACTOR
1	**EUR/USD**
2	**SPREAD ITA-GER 10Y**
3	**UNEMPLOYMENT RATE (2000-2007)**
4	**UNEMPLOYMENT RATE (2016-2022)**
5	**GLOBAL ECONOMIC POLICY UNCERTAINTY**
6	**NATIONAL ECONOMIC POLICY UNCERTAINTY**

As quickly mentioned in the dedicated paragraph, the choice of using a double coefficient for Unemployment Rate is advocated by the change of strategy of the European Central Bank Board through time, more and more accommodative in its crisis management after the Sovereign Debt Crisis. Nowadays, market practitioners generally tend to interpret positively an increase of unemployment, in contrast with what happened in the past, since the European Central Bank will account for it while establishing official rates, oppositely with what happened in the past in similar situations. The intermediate period (2008-2015) has not been considered being it a crossing point, with the coefficient value near to 0.

Consequently, the adopted specification for testing the possibility to model current market returns is illustrated:

$$r_{mkt,t} = b_0 + b_1 * r_{EUR\_USD,t} + \mathrm{I}_{\{2000 \le t \le 2007\}} * b_2 * r_{Unemployment\_Rate,t} + \mathrm{I}_{\{2015 \le t \le 2022\}} * b_3 * r_{Unemployment\_Rate,t} + b_4 * r_{Spread\_ITA-GER\_10Y,t} + b_5 * r_{Glob\_Economic\_Policy\_Uncertainty,t} + b_6 * r_{Nat\_Economic\_Policy\_Uncertainty,t}.$$

Where I is an indicator function taking value:

$$\begin{cases} = 1, \text{if the condition is respected;} \\ = 0, \text{otherwise.} \end{cases}$$

Results

This section aims to describe the main conclusion of the proposed Explanatory Model.

The regression of the Italian Stock Market on the set of the illustrated variables gives as result:

	1 Coefficient	2 P-value
1 Intercept	-9.9853e-04	0.7574
2 EUR/USD	0.2268	0.0577
3 SPREAD ITA-GER	-0.1628	1.4357e-12
4 UNEMPLOYMENT (2000-2007)	-0.4369	0.0757
5 UNEMPLOYMENT (2016-2022)	0.2549	0.0970
6 GLOBAL ECONOMIC POLICY UNCERTAINTY	-0.0731	1.7854e-04
7 NATIONAL ECONOMIC POLICY UNCERTAINTY	-0.0056	0.5770

Comparing the coefficients and the p-values with the previous outcomes of the univariate case:

FACTOR	Coefficient	P-value	R_Squared
EUR/USD	0.4297	0.0015	0.0375
SPREAD ITA-GER 10Y	-0.1874	0	0.2207
UNEMPLOYMENT RATE (2000-2007)	-0.3595	0.1540	0.0213
UNEMPLOYMENT RATE (2016-2022)	0.4472	0.0013	0.0836
GLOBAL ECONOMIC POLICY UNCERTAINTY	-0.1048	0	0.0928
NATIONAL ECONOMIC POLICYUNCERTAINTY	-0.0299	0.0076	0.0268

In general results are the same. The leading conclusion is that all six risk factors present coefficients of the same sign either in the univariate and multivariate case, showing very similar sensitiveness for most of them. In particular, the exchange rate EUR/USD exhibits a weaker coefficient, the Unemployment Rate for the period 2016-2022 a stronger one and the National Economic Policy Uncertainty fades towards zero.

Regarding the significance of coefficients, p-values are notably larger for the entire cluster of regressors. Maximum significance in the joint model endures only for the Spread ITA-GER 10Y and for Global Economic Policy Uncertainty, whereas for National Economic Policy Uncertainty all relevance is lost. The other factors continue to show minimum significance.

About the explanatory ability of the model, it has remarkably increased (= 0.3004) compared to the univariate regressions, following the additional parametrization.

	1 R_Squared
1 Explanatory Model	0.3004

Although the proposed Explanatory Model shows an important R-Squared, the measure let a substantial margin of improvement with the addition of other parameters not considered in the course of this study, possibly of specific national nature because of the lack of previous literature in Italy.

Backtest

After having obtained the statistical information concerning the model, this paragraph offers few insights about the application of findings and the comparison with the real market movements.

As initial step, it is possible to liken the compounded time series of returns to get a visual analysis:

From a first visualization, the goodness of the model appears to be time varying. Later a particularly scarce initial period till the end of the dot-com bubble at the beginning of 2003, the fitted time series has gained steadily relevance, matching properly the market for more than a decade, missing some proficiency only in the last few years.

To have a statistical confirmation of what explained up to this moment, the correlation coefficient between real Italian market returns and fitted market returns may help.

$$Corr\ (r_{mkt,t}, r_{fitted,t}):$$

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 Correlation	0.5481	0.3540	0.6953	0.5411

Correlation analysis validates the findings, showing an initial 2000-2007 period in which the measure is limited (= 0.3540), an intermediate 2008-2015 period where the two time series strongly tend to comove (= 0.6953), and a final 2016-2022 time window whereby the relation is more moderate (= 0.5411) and very near to the overall period value (= 0.5481).

Another element to consider in order to comprehend the precision of the Explanatory Model is its ability in extrapolating at least the sign of monthly market returns. By constructing three additional time series as following:

$$\mathrm{I}_{mkt,t} = \begin{cases} 1, & if\ r_{mkt,t} > 0 \\ 0, & if\ r_{mkt,t} \leq 0 \end{cases}$$

$$\mathrm{I}_{fitted,t} = \begin{cases} 1, & if\ r_{fitted,t} > 0 \\ 0, & if\ r_{fitted,t} \leq 0 \end{cases}$$

$$\mathrm{I}_{Backtest,t} = \mathrm{I}_{mkt,t} - \mathrm{I}_{fitted,t};$$

the objective is achievable. In particular, knowing $\mathrm{I}_{Backtest,t}$ can take value:

$$\mathrm{I}_{Backtest,t} = \begin{cases} 1, & if\ r_{mkt,t} > 0\ \ and\ \ r_{fitted,t} \leq 0 \\ 0, & if\ \mathrm{I}_{\mathrm{mkt,t}} = \mathrm{I}_{fitted,t} \\ -1, & if\ r_{mkt,t} \leq 0\ \ and\ \ r_{fitted,t} > 0 \end{cases},$$

through the counting of times the same indicator is equal to zero, it is possible to retrieve the exact number of months where $\mathrm{I}_{mkt,t} = \mathrm{I}_{fitted,t}$, or, in other terms, the number of months in which $r_{fitted,t}$ and $r_{mkt,t}$ have the same sign.

By dividing the amount by the total number of months of the analysis, $\pi_{2000-2022}$, $\pi_{2000-2007}$, $\pi_{2008-2015}$ and $\pi_{2016-2022}$ are defined as following:

$$\pi_{2000-2022} = \text{CountIF}(\text{I}_{Backtest,2000-2022} = 0)/\text{Count}(\text{I}_{Backtest,2000-2022})$$

$$\pi_{2000-2007} = \text{CountIF}(\text{I}_{Backtest,2000-2007} = 0)/\text{Count}(\text{I}_{Backtest,2000-2007})$$

$$\pi_{2008-2015} = \text{CountIF}(\text{I}_{Backtest,2008-2015} = 0)/\text{Count}(\text{I}_{Backtest,2008-2015})$$

$$\pi_{2016-2022} = \text{CountIF}(\text{I}_{Backtest,2016-2022} = 0)/\text{Count}(\text{I}_{Backtest,2016-2022}).$$

Intuitively, since the probability to get the right sign by chance is 50%, if:

$\pi = 1 \rightarrow$ The Model totally captures the sign of $\text{ret}_{\text{mkt,t}}$;

$\pi > 0.50 \rightarrow$ The Model provides insights on the sign of $\text{ret}_{\text{mkt,t}}$;

$\pi = 0.50 \rightarrow$ The Model does not provide any insight on the sign of $\text{ret}_{\text{mkt,t}}$;

$\pi < 0.50 \rightarrow$ The Model offers erroneous clues on the sign of $\text{ret}_{\text{mkt,t}}$.

The results of such gauge are now displayed:

	1 2000-2022	2 2000-2007	3 2008-2015	4 2016-2022
1 π (Percentage)	0.6868	0.6289	0.7979	0.6216

Analyzing the table, it is possible to state that, in general, the proposed Explanatory Model has properly worked in the period of analysis ($\pi_{2000-2022} = 0.6868$). Anyway, as yet understood in the course of this paragraph, the goodness is always positive, but the level of precision is time-varying if considering sub-periods. As in the correlation test, precision is maximum in the intermediate 2008-2015 period, being the sign of $r_{mkt,t}$ and $r_{fitted,t}$ equal four times out of five (= 0.7979), and weaker in the initial (=0.6289) and final (0.6216) intervals.

FORECASTING MODEL

The building of a Forecasting Multifactor Model answers to the intention of forecasting next movements or trends of the Italian Stock Market.

Following the univariate analyses conducted on single factors in the dedicated chapter, it has been decided to adopt a long-term overlapping model, since most of analyzed regressors exhibited increasingly significance with longer horizons. In particular, returns are aggregated for a period of k equal to 60 months.

The factors found to possess the best predictive ability on future market returns, considering k=60, are the following:

	FACTOR
1	**WTI CRUDE OIL**
2	**UNEMPLOYMENT RATE**
3	**TRADE BALANCE**
4	**CORE INFLATION**
5	**FED FEDERAL FUNDS TARGET RATE US**
6	**SPREAD ITA-GER 10Y**
7	**DEBT/GDP RATIO – SPREAD ITA-GER**

Consequently, the adopted specification for testing the possibility to anticipate market returns is depicted:

$$r_{mkt,t--\rightarrow t+60} = b_0 + b_1 * r_{Oil,t-60--\rightarrow t} + b_2 * r_{Unemployment\_Rate,t-60--\rightarrow t} + b_3 * r_{Trade\_Balance,t-60--\rightarrow t} + b_4 * r_{Core\_Inflation,t-60--\rightarrow t} + b_5 * r_{Fed\_Rate,t-60--\rightarrow t} + b_6 * r_{Spread\_ITA-GER\_10Y,t-60--\rightarrow t} + b_7 * r_{Debt/GDP\_Spread\_ITA-GER,t-60--\rightarrow t} + \varepsilon_{t--\rightarrow t+60}$$

Results

This paragraph has the ambition to illustrate the principal outcomes of the introduce Forecasting Model.

The regression of the overlapped returns from t to t+60 of the Italian Stock Market on the set of illustrated variables from t-60 to t gives as result:

	1 Coefficient	2 P-value
1 Intercept	-0.2938	5.6485e-07
2 WTI OIL	-0.1970	0.0017
3 UNEMPLOYMENT	0.1766	0.1856
4 TRADE BALANCE	-2.5987e-05	0.0875
5 CORE INFLATION	-0.0502	0.3818
6 FED TARGET RATE	-0.0974	1.8358e-04
7 SPREAD ITA-GER 10Y	0.0600	0.0130
8 DEBT/GDP SPREAD ITA-GER	1.0241	2.7200e-06

Comparing the coefficients and the p-values with the previous outcomes in the univariate case:

FACTOR	Coefficient	P-value	R_Squared
WTI CRUDE OIL	-0.5214	0	0.5214
UNEMPLOYMENT RATE	1.0614	0	0.6500
TRADE BALANCE	0.7684	0	0.3060
CORE INFLATION	-0.2763	0	0.0972
FED FEDERAL FUNDS TARGET RATE US	-0.1635	0	0.3075
SPREAD ITA-GER 10Y	0.1412	0	0.1521
DEBT/GDP – SPREAD ITA-GER	1.2136	0	0.4436

In general results are similar. Except for Trade Balance which coefficient tends to zero, the other six risk factors present coefficients of the same sign either in the univariate and multivariate case, showing related sensitiveness. Anyway, all of them exhibit a weaker coefficient compared to that shown in the univariate case.

Regarding the significance of coefficients, it remains maximum only for WTI Oil, FED Target Rate US and Debt/GDP – SPREAD ITA-GER, whereas the p-values associated to the other factors are importantly larger, especially for Unemployment Rate and Core Inflation.

The explanatory ability of the model, as consequence of the additional parametrization, has significantly increased (= 0.8491) compared to the univariate regressions, showing that most of variability of the five-years aggregate market returns is explained by the aggregated performance of the adopted set of regressors in the previous five years.

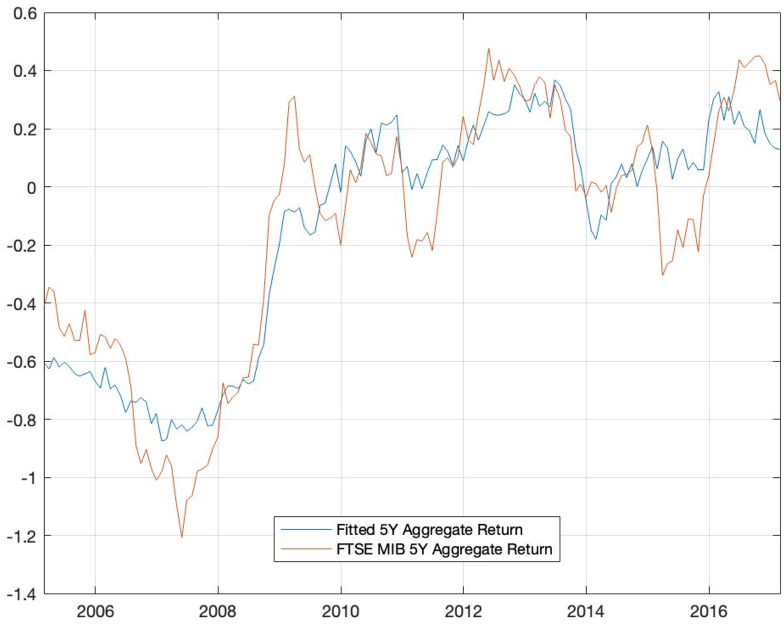
	1 R_Squared
1 Explanatory Model	0.8491

However, since the proposed Forecasting Model shows an exceptional high R-Squared, the possibility of overfitting the market is really concrete and, for this reason, an out-of-sample would be required in the next future to further validate the model.

Backtest

After having examined the results concerning the regression related to the model, this section presents a comparison between the fitted time series of aggregated returns and the actual past market movements.

As introductory step, it is possible to visualize the two time-series of returns, that are jointly available from January 2005 to March 2017 (The fitted time series cannot have the first 60 months of history, whereas the actual time series do not own the last 60 months):



By inspecting the image, the kindness of the Forecasting Model appears to be excellent. The Fitted 5Y Aggregate Return is able to track incredibly well the FTSE MIB 5Y Aggregate Return for the entire period, without moments of particular weakness.

To prove statistically what explicated, the correlation coefficient between the real Italian market aggregate returns and the fitted market aggregate returns is employed:

$$Corr\ (r_{mkt,t--\rightarrow t+60}, r_{fitted,t--\rightarrow t+60})$$

	1 2005-2017
1 Correlation	0.9215

The analysis of correlation confirms the findings, showing a huge correlation coefficient for the whole period (=0.9215), very near to one. The actual time-series and the fitted one have a very strong statistical relationship and, in practice, comove.

As in the case of the Explanatory Model, to properly comprehend the precision of the Forecasting Model, it is possible to test its ability of understanding at least the sign of the next five years aggregate return as of today given the performances of the set of regressors in the previous five years. In order to success in this intent, three additional time series are established:

$$\mathrm{I}_{mkt,t} = \begin{cases} 1, & if\ r_{mkt,t--\rightarrow t+60} > 0 \\ 0, & if\ r_{mkt,t--\rightarrow t+60} \leq 0 \end{cases}$$

$$\mathrm{I}_{fitted,t} = \begin{cases} 1, & if\ r_{fitted,t--\rightarrow t+60} > 0 \\ 0, & if\ r_{fitted,t--\rightarrow t+60} \leq 0 \end{cases}$$

$$\mathrm{I}_{Backtest,t} = \mathrm{I}_{mkt,t} - \mathrm{I}_{fitted,t};$$

Given the definition, $\mathrm{I}_{Backtest,t}$ can value:

$$\mathrm{I}_{Backtest,t} = \begin{cases} 1, & if\ r_{mkt,t--\rightarrow t+60} > 0\ and\ r_{fitted,t--\rightarrow t+60} \leq 0 \\ 0, & if\ \mathrm{I}_{\mathrm{mkt,t}} = \mathrm{I}_{fitted,t} \\ -1, & if\ r_{mkt,t--\rightarrow t+60} \leq 0\ and\ r_{fitted,t--\rightarrow t+60} > 0 \end{cases}.$$

By counting the number of times the indicator is equal to zero, it is possible to retrieve the exact number of five years aggregate returns whereby $\mathrm{I}_{mkt,t} = \mathrm{I}_{fitted,t}$, or, in other terms, the number of months in which $r_{mkt,t--\rightarrow t+60}$ and $r_{fitted,t--\rightarrow t+60}$ have the same sign.

By dividing the amount by the total number of overlapped returns of the analysis, $\pi_{2005-2017}$, is defined as following:

$$\pi_{2000-2022} = \mathrm{CountIF}(\mathrm{I}_{Backtest,2000-2022} = 0)/\mathrm{Count}(\mathrm{I}_{Backtest,2000-2022}).$$

Rationally, since the probability to get the right sign of $r_{mkt,t--\rightarrow t+60}$ five years before by chance is 50%, if:

$\pi = 1 \rightarrow$ The Model always predicts the sign of $\mathrm{ret}_{\mathrm{mkt,t--\rightarrow t+60}}$;

$\pi > 0.50 \rightarrow$ The Model provides insights on the sign of $\mathrm{ret}_{\mathrm{mkt,t--\rightarrow t+60}}$;

$\pi = 0.50 \rightarrow$ The Model does not offer insight on the sign of $\mathrm{ret}_{\mathrm{mkt,t--\rightarrow t+60}}$;

$\pi < 0.50 \rightarrow$ The Model tenders wrong clues on the sign of $\mathrm{ret}_{\mathrm{mkt,t--\rightarrow t+60}}$.

The result of such measure is now exhibited:

	1 2005-2017
1 π (Percentage)	0.7931

As confirmation of what observed through visualization and correlation analysis, the percentage of times the fitted time-series shows equal sign of the actual time series is very elevated ($\pi = 0.7931$), suggesting that the degree of precision of the model is considerable.

CONCLUSIONS

In order to attain a significant comprehension of stock market movements, an analysis of the Italian Stock Market from 2000 to 2022 has been conducted to understand the principal macroeconomic levers able to explain current and/or future FTSE MIB returns.
The factors have been mainly suggested by extensive previous literature based in other times and geographies. Successively, the Italian Stock Market has been regressed against the literature suggestions one by one, either using monthly simple and lagged returns, in order to receive insights about the explanatory and the forecasting ability of the analyzed factors.
In a second moment, the most reasonable macroeconomic factors showing the best statistical properties have been selected to propose two different APT models, one aimed to explain current market returns and another to attempt to forecast five years aggregate market returns.
Unemployment Rate, Exchange Rate EUR/USD, Spread ITA-GER 10Y, Global Economic Uncertainty and Italian Economic Uncertainty have exhibited the greatest ability in explaining current Italian market returns. The results of the backtest accomplished on the Explanatory Model have delivered positive results in its scope, showing the goodness of the specification but leaving space to further improvements.
WTI Crude Oil, Unemployment Rate, Balance of Trade, Core Inflation, FED Federal Funds Target Rate US have shown the greatest ability in forecasting five years aggregate Italian market returns. The results of the backtest accomplished on the Forecasting Model have provided very excellent outcomes in its aim, exhibiting the outstanding goodness of the model.
These findings may have substantial implications for the decision-making process of investors willing to attempt to overperform the market through timing strategies, but also of market policy makers and supervisors that may be able to anticipate market crises and adequate their behavior consequently.

APPENDIX

This Appendix is dedicated to reveal the key points of the MATLAB code (Version R2022a) used to perform the various analysis present in this research.

An exemplificative code for testing the explanatory power of one of the analyzed macro-factors in “Retrieving the Macro-Factors” (WTI Crude Oil) is shown:

```
%% OIL

%PLOT THE COMPARISON BETWEEN FTSE MIB AND OIL PRICE TIME-SERIES:
yyaxis left
plot(Dates,OIL)
hold on
yyaxis right
plot(Dates,FTSEMIB)
grid on
legend ('CRUDE WTI OIL', 'FTSE MIB')
hold off

%SET THE THREE SUB-PERIODS:
t_2000_2007 = [1:97]'; %2000-2007
t_2008_2015 = [98:191]'; %2008-2015
t_2016_2022 = [192:265]'; %2016-2022

%PLOT THE COMPARISON BETWEEN FTSE MIB AND OIL RETURN TIME-SERIES:
yyaxis left
plot(Dates(2:end),r_oil)
hold on
yyaxis right
plot(Dates(2:end),r_mkt)
grid on
legend ('CRUDE WTI OIL ret', 'FTSE MIB ret')
hold off

%REGRESS THE MARKET OVER OIL FOR THE ENTIRE PERIOD OF ANALYSIS:
mkt_oil= fitlm(r_oil,r_mkt)
Constant= mkt_oil.Coefficients.Estimate(1);
Coefficient= mkt_oil.Coefficients.Estimate(2);
p_value= mkt_oil.Coefficients.pValue(2);
R_2= mkt_oil.Rsquared.Ordinary;

%REGRESS THE MARKET OVER OIL FOR THE 2000-2007 PERIOD:
mkt_oil_1= fitlm(r_oil(t_2000_2007),r_mkt(t_2000_2007))
Constant_1= mkt_oil_1.Coefficients.Estimate(1);
Coefficient_1= mkt_oil_1.Coefficients.Estimate(2);
p_value_1= mkt_oil_1.Coefficients.pValue(2);
R_2_1= mkt_oil_1.Rsquared.Ordinary;

%REGRESS THE MARKET OVER OIL FOR THE 2008-2015 PERIOD:
mkt_oil_2=fitlm(r_oil(t_2008_2015),r_mkt(t_2008_2015))
Constant_2= mkt_oil_2.Coefficients.Estimate(1);
```

```
Coefficient_2= mkt_oil_2.Coefficients.Estimate(2);
p_value_2= mkt_oil_2.Coefficients.pValue(2);
R_2_2= mkt_oil_2.Rsquared.Ordinary;

%REGRESS THE MARKET OVER OIL FOR THE 2016-2022 PERIOD:
mkt_oil_3=fitlm(r_oil(t_2016_2022),r_mkt(t_2016_2022))
Constant_3= mkt_oil_3.Coefficients.Estimate(1);
Coefficient_3= mkt_oil_3.Coefficients.Estimate(2);
p_value_3= mkt_oil_3.Coefficients.pValue(2);
R_2_3= mkt_oil_3.Rsquared.Ordinary;

%BUILD THE STATISTICAL TABLE:
Statistics ={'Mean FTSE MIB';'Std MIB';'Mean/Std FTSE MIB';'Mean OIL';'Std
OIL';'Mean/Std OIL';'Correlation'};
Periods = {'2000-2022','2000-2007','2008-2015','2016-2022'};
A=[mean(r_mkt);std(r_mkt);mean(r_mkt)/std(r_mkt);mean(r_oil);std(r_oil);me
an(r_oil)/std(r_oil);corr(r_mkt,r_oil)];
B=[mean(r_mkt(t_2000_2007));std(r_mkt(t_2000_2007));mean(r_mkt(t_2000_2007
))/std(r_mkt(t_2000_2007));...

mean(r_oil(t_2000_2007));std(r_oil(t_2000_2007));mean(r_oil(t_2000_2007))/
std(r_oil(t_2000_2007));corr(r_mkt(t_2000_2007),r_oil(t_2000_2007))];
C=[mean(r_mkt(t_2008_2015));std(r_mkt(t_2008_2015));mean(r_mkt(t_2008_2015
))/std(r_mkt(t_2008_2015));...

mean(r_oil(t_2008_2015));std(r_oil(t_2008_2015));mean(r_oil(t_2008_2015))/
std(r_oil(t_2008_2015));corr(r_mkt(t_2008_2015),r_oil(t_2008_2015))];
D=[mean(r_mkt(t_2016_2022));std(r_mkt(t_2016_2022));mean(r_mkt(t_2016_2022
))/std(r_mkt(t_2016_2022));...

mean(r_oil(t_2016_2022));std(r_oil(t_2016_2022));mean(r_oil(t_2016_2022))/
std(r_oil(t_2016_2022));corr(r_mkt(t_2016_2022),r_oil(t_2016_2022))];

T=table([A],[B],[C],[D],'RowNames',Statistics,'VariableNames',Periods)

%BUILD THE REGRESSION TABLE:
Statistics2 ={'Constant';'Coefficient';'P-value';'R-2'};
A2=[Constant;Coefficient;p_value;R_2];
B2=[Constant_1;Coefficient_1;p_value_1;R_2_1];
C2=[Constant_2;Coefficient_2;p_value_2;R_2_2];
D2=[Constant_3;Coefficient_3;p_value_3;R_2_3];

T2=table([A2],[B2],[C2],[D2],'RowNames',Statistics2,'VariableNames',Period
s)
```

An exemplificative code for testing the forecasting power in "Retrieving the Macro-Factors" of one of the analyzed macro-factors (WTI Crude Oil) is exhibited:

```
%% OIL

LAG= [1;6;12;24;36;60]; %Set the months of LAG

r_mkt = diff(log(FTSEMIB));
N= size(r_mkt,1);

%BUILD THE DIFFERENT TIME-SERIES OF AGGREGATE MARKET RETURNS (T--→T+K(LAG))
(ONE FOR EACH LAG):
r_y=[NaN(N,size(LAG,1))];
for j=1:size(LAG,1)
    for t=1:(N-LAG(j))
        r_y(t,j)= sum(r_mkt(t+1:t+LAG(j),1));
    end
end

%BUILD THE DIFFERENT TIME-SERIES OF AGGREGATE OIL RETURNS (T-K(LAG)--→T)
(ONE FOR EACH LAG):
r_oil = diff(log(OIL));
r_x=[NaN(N,size(LAG,1))];
for j=1:size(LAG,1)
    for t=(LAG(j)+1):size(r_oil,1)
        r_x(t,j)= sum(r_oil(t+1-LAG(j):t));
    end
end

% REGRESS THE MARKET AGGREGATE RETURN (T--→T+K(LAG)) AGAINST THE OIL
AGGREGATE RETURN (T-K(LAG)--→T):
beta=[];
SE=[];
constant=[];

for i=1:size(LAG,1)
    regression= fitlm(r_x(1+LAG(i):end-LAG(i),i),r_y(1+LAG(i):end-
LAG(i),i))
    R_Square(:,i)=regression.Rsquared.Ordinary;
    p_value(:,i)=regression.Coefficients.pValue;
    beta(:,i)= regression.Coefficients.Estimate;
end

%CONSTRUCT THE REGRESSION TABLE:
Statistics ={'Constant';'Coefficient';'P-value';'R-2'};
Periods = {'k=1','k=6','k=12','k=24','k=36','k=60'};
A=[beta(1,1);beta(2,1);p_value(2,1);R_Square(1,1)];
B=[beta(1,2);beta(2,2);p_value(2,2);R_Square(1,2)];
C=[beta(1,3);beta(2,3);p_value(2,3);R_Square(1,3)];
D=[beta(1,4);beta(2,4);p_value(2,4);R_Square(1,4)];
E=[beta(1,5);beta(2,5);p_value(2,5);R_Square(1,5)];
F=[beta(1,6);beta(2,6);p_value(2,6);R_Square(1,6)];

T=table([A],[B],[C],[D],[E],[F],'VariableNames',Periods,'RowNames',Statist
ics)
```

The code for building and backtesting the Explanatory Model proposed in “Identifying the Models” is shown:

```
%% EXPLANATORY MODEL SPECIFICATION

%FORM THE VECTOR OF REGRESSORS:
Factors=
[r_eur_usd,r_spread,r_unemployment_2000_2007,r_unemployment_2016_2022,...
    r_global_unc,r_national_unc];

%REGRESS THE MARKET ON THE SET OF REGRESSORS:
Regression= fitlm(Factors,r_mkt)
Coefficients= Regression.Coefficients.Estimate;
p_value= Regression.Coefficients.pValue;
R_2= Regression.Rsquared.Ordinary;
y=Regression.Fitted;

%BUILD THE REGRESSION TABLE:
Statistics ={'Coefficient','P-value'};
A=[Coefficients];
B=[p_value];
Factor = {'Intercept';'EUR/USD';'SPREAD ITA-GER';'UNEMPLOYMENT (2000-
2007)';'UNEMPLOYMENT (2016-2022)';'GLOBAL ECONOMIC POLICY
UNCERTAINTY';'NATIONAL ECONOMIC POLICY UNCERTAINTY'};
T=table([A],[B],'RowNames',Factor,'VariableNames',Statistics)

%BUILD THE R_SQUARED TABLE:
Statistics ={['R_Squared']};
A=[R_2];
Factor = {'Explanatory Model'};
T2=table([A],'RowNames',Factor,'VariableNames',Statistics)


%% BACKTEST

%VISUALIZE THE RETURN FITTED TIME-SERIES AGAINST THE FTSE MIB TIME-SERIES:
plot(Dates(2:end),y)
plot(Dates(2:end),r_mkt)

%CORRELATION ANALYSIS
correlation= corr(r_mkt,y);
correlation_2000_2007= corr(r_mkt(t_2000_2007),y(t_2000_2007));
correlation_2008_2015= corr(r_mkt(t_2008_2015),y(t_2008_2015));
correlation_2016_2022= corr(r_mkt(t_2016_2022),y(t_2016_2022));

Statistics ={'2000-2022','2000-2007','2008-2015','2016-2022'};
Factor = {'Correlation'};
T3=table(correlation,correlation_2000_2007,correlation_2008_2015,correlati
on_2016_2022,'RowNames',Factor,'VariableNames',Statistics)

%BUILD THE NORMALIZED TIME-SERIES FOR EACH SUB PERIOD:
n=size(y,1);
Price_mkt=[100];
Price_y=[100];
r_mkt(1)=0;
for i=2:n+1
    Price_mkt(i,1)= Price_mkt(i-1,1)*(1+r_mkt(i-1));
    Price_y(i,1)= Price_y(i-1,1)*(1+y(i-1));
```

```
end

Price_mkt_2000_2007=[100];
Price_y_2000_2007=[100];
for i=2:98
    Price_mkt_2000_2007(i,1)= Price_mkt_2000_2007(i-1,1)*(1+r_mkt(i-1));
    Price_y_2000_2007(i,1)= Price_y_2000_2007(i-1,1)*(1+y(i-1));
end

Price_mkt_2008_2015=[100];
Price_y_2008_2015=[100];
for i=99:192
    Price_mkt_2008_2015(i-97,1)= Price_mkt_2008_2015(i-98,1)*(1+r_mkt(i-
1));
    Price_y_2008_2015(i-97,1)= Price_y_2008_2015(i-98,1)*(1+y(i-1));
end

Price_mkt_2016_2022=[100];
Price_y_2016_2022=[100];
for i=193:266
    Price_mkt_2016_2022(i-191,1)= Price_mkt_2016_2022(i-192,1)*(1+r_mkt(i-
1));
    Price_y_2016_2022(i-191,1)= Price_y_2016_2022(i-192,1)*(1+y(i-1));
end

%VISUALIZE THE NORMALIZED FITTED TIME-SERIES AGAINST THE FTSE MIB TIME-
SERIES FOR EACH SUB-PERIOD:
plot(Dates,Price_y)
grid on
hold on
plot(Dates,Price_mkt)
legend ('Fitted', 'FTSE MIB')
title('2000-2022')
hold off

plot(Dates(1:98),Price_y_2000_2007)
grid on
legend
hold on
plot(Dates(1:98),Price_mkt_2000_2007)
legend ('Fitted', 'FTSE MIB')
title('2000-2007')
hold off

plot(Dates(99:193),Price_y_2008_2015)
grid on
legend
hold on
plot(Dates(99:193),Price_mkt_2008_2015)
legend ('Fitted', 'FTSE MIB')
title('2008-2015')
hold off

plot(Dates(194:266),Price_y_2016_2022(1:end-2))
grid on
legend
hold on
plot(Dates(194:266),Price_mkt_2016_2022(1:end-2))
legend ('Fitted', 'FTSE MIB')
```

```
title('2016-2022')
hold off

%CONSTRUCT THE INDICATORS:
I_mkt=[];
I_y=[];
for i=1:n
    if r_mkt(i)>0
        I_mkt(i)=1;
    else  I_mkt(i)=0;
    end

    if y(i)>0
        I_y(i)=1;
    else  I_y(i)=0;
    end
end

I_mkt=I_mkt';
I_y=I_y';

%BACKTEST THE INDICATOR:
Backtest=I_mkt-I_y;

count=0;
for i=1:n
    if Backtest(i)==0;
        count=count+1;
    end
end

count_2000_2007=0;
for i=1:97
    if Backtest(i)==0;
        count_2000_2007=count_2000_2007+1;
    end
end

count_2008_2015=0;
for i=98:191
    if Backtest(i)==0;
        count_2008_2015=count_2008_2015+1;
    end
end

count_2016_2022=0;
for i=192:265
    if Backtest(i)==0;
        count_2016_2022=count_2016_2022+1;
    end
end

Percentual=count./size(Backtest,1);
Percentual_2000_2007= count_2000_2007./size(Backtest(t_2000_2007),1);
Percentual_2008_2015= count_2008_2015./size(Backtest(t_2008_2015),1);
Percentual_2016_2022= count_2016_2022./size(Backtest(t_2016_2022),1);
```

```
%PUT THE RESULTS IN  TABLE:
Time ={'2000-2022','2000-2007','2008-2015','2016-2022'};
Factor = {'π (Percentage)'};
T4=table(Percentual,Percentual_2000_2007,Percentual_2008_2015,Percentual_2
016_2022,'RowNames',Factor,'VariableNames',Time)
```

The code for building and backtesting the Forecasting Model proposed in “Identifying the Models” is exhibited:

```
% AGGREGATE MARKET RETURNS (T-->T+60):
r_mkt = diff(log(FTSEMIB));
N= size(r_mkt,1);
LAG= 60; % Lag 5 years adopted

r_y=[NaN(N,size(LAG,1))];
for j=1:size(LAG,1)
    for t=1:(N-LAG(j))
        r_y(t,j)= sum(r_mkt(t+1:t+LAG(j),1));
    end
end

% AGGREGATE THE RETURNS OF THE SET OF REGRESSORS (T-60-->T):
Factors= [r_oil, r_unemployment, r_trade, r_inflation, r_fed, r_spread,
r_debt_gdp];
R_X=[NaN(N,size(Factors,2))];

for j= 1:size(Factors,2)
    for t=(LAG+1):size(Factors,1)
       R_X(t,j)= sum(Factors(t+1-LAG:t,j));
    end
end

%% FORECASTING MODEL SPECIFICATION

%REGRESS THE MARKET AGGREGATE RETURN (T-->T+K) AGAINST THE SET OF
AGGREGATE RETURNS:
%OF REGRESSORS (T-K-->T):
Regression= fitlm(R_X,r_y)
Coefficients= Regression.Coefficients.Estimate;
p_value= Regression.Coefficients.pValue;
R_2= Regression.Rsquared.Ordinary;
modeled_ret= Regression.Fitted;

%BUILD THE REGRESSION TABLE:
Statistics ={'Coefficient','P-value'};
A=[Coefficients];
B=[p_value];
Factor = {'Intercept';'WTI OIL';'UNEMPLOYMENT';'TRADE BALANCE';'CORE
INFLATION';...
    'FED TARGET RATE';'SPREAD ITA-GER 10Y';'DEBT/GDP SPREAD ITA-GER'};
T=table([A],[B],'RowNames',Factor,'VariableNames',Statistics)

%BUILD THE R_SQUARED TABLE:
Statistics ={['R_Squared']};
A=[R_2];
```

```
Factor = {'Explanatory Model'};
T2=table([A],'RowNames',Factor,'VariableNames',Statistics)
%% BACKTEST

%NORMALIZE THE THE FITTED TIME-SERIES AND THE MARKET TIME-SERIES:
r_y=r_y(61:end-60);
modeled_ret=modeled_ret(61:end-60);

%PLOT AND COMPARE THE TIME-SERIES:
plot(Dates(62:end-60),modeled_ret)
hold on
plot(Dates(62:end-60),r_y)
grid on
legend ("Fitted 5Y Aggregate Return","FTSE MIB 5Y Aggregate Return")
hold off

%BUILD THE INDICATORS:
n=size(r_y,1);
I_y=[];
I_modeled=[];
for i=1:n
    if r_y(i)>0
        I_y(i)=1;
    else  I_y(i)=0;
    end

    if modeled_ret(i)>0
        I_modeled(i)=1;
    else  I_modeled(i)=0;
    end
end

I_y=I_y';
I_modeled=I_modeled';

%BACKTEST THE INDICATOR:
Backtest=I_y-I_modeled;

count=0;
for i=1:n
    if Backtest(i)==0;
        count=count+1;
    end
end

Percentual=count./size(Backtest,1);

%PUT THE RESULTS IN  TABLE:
correlation=corr(r_y,modeled_ret)
Statistics ={'2005-2017'};
Factor = {'Correlation'};
T3=table(correlation,'RowNames',Factor,'VariableNames',Statistics)


Statistics ={'2005-2017'};
Factor = {'π (Percentage)'};

T4=table(Percentual,'RowNames',Factor,'VariableNames',Statistics)
```

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