



**SCHOOL OF ECONOMICS AND MANAGEMENT**  
Lund University  
Department of Economics

**Master Thesis**  
**June 2007**

**Stock Market Timing and Government Bond Yield Spread:  
An Emerging and Established Markets Analysis**

**Authors: *Giuseppe Pagliano***

***Roman Tokarev***

**Tutor: *Hossein Asgharian***

# Contents

Chapter 1. Introduction	5
Chapter 2. Russian and Italian Stock Markets Development	10
2.1. Russian stock market	10
2.2. Italian stock market	13
Chapter 3. The Data	15
3.1. Overview and sources	15
3.2. Italian market data	15
3.3. Russian market data	16
Chapter 4. Methodology	17
4.1. The probit models theory	17
4.2. Maximum likelihood estimation of probit models	18
4.3. Goodness-of-fit tests for probit models	19
4.3.1. The Hosmer-Lemeshow test	19
4.3.2. The Andrews test	20
4.4. The probit model to forecast bear market	20
4.5. Model extensions	21
4.6. Forecasting	22
4.7. Market timing testing	23
Chapter 5. Russian Stock Market Timing	25
5.1. Basic model estimation	25
5.2. Introducing country risk premium	27
5.3. The role of oil prices	28
5.4. Estimation of the final model	31
5.5. Model testing	32
5.5.1. Testing the coefficient significance	32
5.5.2. Goodness-of-fit tests	33
5.6. Market timing returns	33
5.7. Market timing testing	35
Chapter 6. Italian Stock Market Timing	37
6.1. Dependent binary variable choice	37
6.2. The U.S. spread as explanatory variable	38
6.3. Estimation of the final model	39
6.4. Model testing	41
6.4.1. Testing the coefficient significance	41
6.4.2. Goodness-of-fit tests	42
6.5. Market timing returns	42

6.6. Market timing testing	43
Conclusions	45
References	48

## **Preamble**

The aim of the paper is to time the stock market by using probit modelling. We will accomplish this task by testing the significance of different financial variables. The yield spread, which has already been proved to be effective for several established markets, will play a central role in our analysis.

Primarily we will extend the analysis of Liu, Resnick and Shoesmith (2004) to verify whether the slope of the U.S. yield curve can offer important information also to time the Italian stock market, thus providing the opportunity to construct a better portfolio as compared to the benchmark of the buy-and-hold strategy on the stock market. However, we will also attempt to test a modified version of the model for the emerging Russian stock market and we will eventually test the effectiveness of other financial variables within a framework of out-of-sample forecasting. Moreover, we will change some parameters in the model, such as the definition of the dependent binary variable or the frequency of the data, and explain the changes in the empirical findings.

Contrary to the academic prospective which is futile to beat the market and given the objective difficulties in finding effective market timing strategy, we want to show how a relatively simple model can offer a fairly reliable solution to the choice of timing the investments on the stock market.

## Chapter 1. Introduction

The origin of interest in such research comes from a group of related observations. First of all, primary driver of the expected stock returns can be considered the firms' earnings growth, which are recognized pro-cyclical variables. This would mean, as pinpointed by Siegel (1998), that an investor capable of forecasting the evolution of the business cycle could exploit this advantage by timing the market and therefore obtaining superior returns. Siegel estimated the benefit of being capable to forecast turning points in the U.S. economy and then switching in and out of stock and T-bills as an excess return of 4.8% over the buy-and-hold strategy.

Second, the relationship between the shape of the yield curve and the level of economic activity has been the object of several studies by different economists (Chen, Roll and Ross 1986; Harvey 1989). In fact, as the historical analysis shows, the yield curve has often a negative slope before economic recession.

Several arguments have been traditionally put forward to justify the link between economic growth and the yield spread. Here we will provide some theoretical background about it. First, the "expectations hypothesis" of the term structure of interest rates postulates that the interest rate of the long term bond should contain information about the future level of short term interest rates expected by the market participants. Further, the market expectations are assumed to be systematically correct. In other words, low long term rates in the present predict future short term rates to be low. In general, periods of recession are associated with a low level of the short term interest rates. This can be explained either by the fact that generally inflation and output are negatively correlated, or through the comprehension of the behavior of the policy makers, that tend to accommodate the recession by lowering the interest rates – "counter-cyclical monetary policy". Thus, a flat or inverted yield curve generally precedes a recession. Obviously, a steep yield curve would be interpreted the other way around. Another possible argument is that the current monetary policy can affect directly the output in the future.

An alternative theory, namely the Preferred Habitat Term Structure Hypothesis, can offer a further insight on the issue. In particular, since the risk premium required by people to hold long term bonds can increase in time of recession due to the uncertainty about their future income, the

yield spread would therefore exhibit a cyclical behavior. In other words, the risk premium would contain information about the stage of the business cycle.

The work of Estrella and Mishkin (1996, 1998) strongly corroborates the theoretical arguments for the importance of the yield spread as a predictor of economic recession with the empirical analysis. Using a probit model for forecasting U.S. economic recession, they found that, among the financial variables, the yield spread and the stock market returns work best as leading indicators. More specifically, the yield spread between the 3 month and the 10 year bonds is an effective variable for predicting the U.S. economic recession for two quarters or beyond in advance.

More recently, a relevant number of articles confirm the informational content of the yield spread by using a more heterogenous and sophisticated set of econometric techniques. Ahrens (2002) shows that modelling the spread as a two-state switching variable and applying the Markov-switching filter does not significantly improve the forecasting ability of the spread.

Moneta (2005) analyzes the role of the yield spread within Europe as a predictor of recession by using the standard probit model developed by Estrella and Mishkin (1998), as compared to the modified version proposed by Dueker (1997), which involves the addition of a lagged dependent variable. The findings emphasize that the best spread to be used is the difference between the ten year and the three month interest rates and confirm the effectiveness of the modification of Dueker (1997) in terms of forecasting power.

Furthermore, several papers show that the yield spread is one of the most important variables when it comes to explain the variance of the stock returns. For instance, Campbell (1987) found that the yield spread is the key variable in predicting the time-varying stock risk premia.

Nonetheless, just few papers shed light on the issue of whether the set of information which the government bond market subsumes can be effectively employed to time the stock market in order to form investment portfolios with superior characteristics in terms of risk and return. The findings of the work by Estrella and Mishkin (1998) that the slope of the yield curve is an effective leading indicator available at any lag are the starting point for the research of Resnick and Shoesmith (2002), who developed a probit model to predict the U.S. bear markets by using the yield spread as explanatory variable. This implies the assumption that the stock market is

switching from one state to another, given the fact that the dependent variable will be binary. Resnick and Shoesmith do not clarify whether this can be justified on theoretical basis when analyzing the stock market, while Estrella and Mishkin point out the empirical work of Hamilton (1989) to state that “it makes sense to think of the economy as evolving differently within distinct discrete states”. However, Resnick and Shoesmith (2002) define the binary variable as at least 6 months of decreasing stock market, consistently with the definition of economic recession lasting at least for two quarters, implicitly assuming a very strict correspondence between the duration of trends on the stock market and the dynamics of the GDP. In their research, they find that the probit market timing strategy in out-of-sample forecasting would have been able to provide an annual return of 16.46%, versus a buy-and-hold strategy on the U.S. stock market of 14.17%.

In a more recent article, Liu, Resnick and Shoesmith (2004) extended the research on other international stock markets. Their conclusion is that in general the U.S. yield spread contains relevant information to be used within the probit modelling framework to time many established stock markets, such as the Australian, British, French, Belgian, German and Dutch. On the other hand, the home-country slope of the yield curve does not turn out to be an effective explanatory variable.

The result is not particularly surprising, when considering the high level of correlation among many stock markets and the strong influence which a big economy can have on a smaller one. In fact, as Liu, Resnick and Shoesmith explain, there is considerable amount of empirical evidence which justifies this finding. Fisher and Palasvirta (1990) document that the U.S. market plays a leading role in the price determination of almost every other stock market in the world. Lin, Engle and Ito (1994) studied the deep economic relationships binding the different economies to conclude that, given the strong reciprocal influence exerted through international trade and investments, changes in the fundamentals of one country are likely to have significant consequences on the others. Of particular relevance, Neely (2001) arguments that, since different countries react to similar macroeconomic shocks and they generally want to maintain a stable level of exchange rates, this could justify the phenomenon that the changes in the interest rates of big economy such the U.S. generally predict a change in the smaller ones.

More recently, another article of Yang and Bessler (2004) reinforced the considerable amount of empirical evidence supporting the role of price leadership played by the U.S. stock market. The

authors focused their analysis on the price relationship among nine major stock future indices. Of particular interest, they analyzed the stock future index because of the difficulties a typical investor would face in replicating the index, such as tracking errors, size of the initial investment and transaction costs. Moreover, a further rationale to their research is that, as proved in Kawaller and al. (1987), stock index futures lead the movements of the spot indices. By implementing innovative econometric technique Yang and Bessler (2004) show that the U.S. stock market affects the behavior of the other markets at any time horizons.

Finally, we would like to point out the importance of identifying the turning point in the business cycle to time the stock market, as previously argued by Siegel (1998), since this is the primary rationale for using the yield spread. There is a consistent evidence which emphasizes the idea that to be able to forecast the stock market returns, it is extremely useful to be able to predict the evolution of the macroeconomic fundamentals. For example, Gerlach (2002) using high-frequency data from 1988 to 2002, found that “the economic volatility, defined as squared deviations of the quarterly gross domestic product (GDP) growth rate from its long-run trend, can explain about half of the variation in S&P 500-stock index quarterly volatility”.

The primary purpose of our analysis is to identify clear signals to be used in order to construct a portfolio characterized by superior expected returns coupled to a smaller risk. Specifically, given that the outcome of the probit forecasting is a series of probabilities, we need some criteria to filter this series. In other words, as suggested by Resnick and Shoesmith (2002), we will exit the stock market every time the forecasted probability of downturn one period ahead results inferior to a certain value. In such a case, we will switch from a hypothetical fund invested in the stock index and use the proceeds for buying a short term T-bill (ideally, a domestic treasury bill). On the other hand, we will enter the stock market again once the probability of a bear market becomes lower than the filtering level. In general, given the smaller volatility of the short term bond market, our investment strategy will show a lower level of volatility as compared to the buy-and-hold strategy on the stock market.

We acknowledge that the choice of the level of the filtering probability is a critical issue in order to evaluate the performance of the probit market timing strategies. However, we will try to show for which level our model could work.



The next chapter provides a short history of the Russian and Italian stock market development. Chapter three describes the data obtained for empirical testing of the model and certain peculiarities of Russian and Italian stock market data. In Chapter 4 we provide the reader with a theoretical background of probit models, an overview of the probit model described by Resnick and Shoesmith (2002) and a discussion about choosing possible regressors and the most appropriate dependent variables to be inserted into the model. The main chapters, five and six, cover our probit models for forecasting the bear market in Russia and Italy respectively, and their testing. They also contain our calculations of buy-and-hold and market timing strategy returns, and explanations of the results.

## **Chapter 2. Russian and Italian Stock Markets Development**

### ***2.1. Russian stock market<sup>1</sup>***

The history of the Russian stock market begins in 1992 with the privatization of the state property after the fall of the Soviet Union. In September 1995 the stocks were first quoted electronically at the first Russian stock exchange – Russian Trading System (RTS), however the actual deals were conducted by traders by telephone. This was an analogue of NASDAQ trading system. Also in September 1995 the first national stock index – RTS Index appeared. The secondary market was highly liquid, but it only involved about 100 companies. These 100 companies included the largest and most enterprising companies, with demand for their shares coming from both domestic and international investors.

For several years RTS was the only stock exchange for Russian stock trading between residents and non-residents. After 1997 it yielded precedence to Moscow Interbank Currency Exchange (MICEX). RTS was implementing its electronic trading system for too long, while MICEX in March 1997 started to quote stocks, set up deals and settle them electronically with 100% preliminary depositing of assets. From the very beginning, the market demonstrated considerable growth both in terms of trading volumes and in terms of the number of participants. In December 1997, the daily average turnover in stocks and regional bonds amounted to over 8,5 million dollars. Fifty stocks of 33 corporate issuers and 100 bonds of 40 entities of the Russian Federation (RF) were circulating on MICEX. The stock exchange began to attract private investors' resources to the stock market. Private investors were enabled to participate in stock trading using the electronic trading system.

The first government zero-coupon bills were issued in May 1993 and the initial placement was conducted by MICEX on May 17, 1993. Regular secondary trading started in June, where 24 banks and financial institutions, granted the status of market dealer by the Central Bank, took part. In October the market was made accessible for private individuals. In 1993 nine auctions were conducted for initial bills allocation, where 2.3 million bills were sold, while turnover of deals on secondary market reached USD 90 mln, turning them into a security with the highest liquidity rate on the Russian stock market. The bond market became one of the major

---

<sup>1</sup> The facts and figures given in this section are based on MICEX history report (2005) and statistics of Bank of Russia (<http://www.cbr.ru/eng/main.asp>).

instruments of the government and the Bank of Russia to perform centralized government borrowings of available funds from commercial banks, enterprises and population for the purpose of non-inflation financing of the state budget, as well as for conducting monetary and credit policy by controlling the money stock in circulation and creating reliable assets with high liquidity for the banking system.

In June 1995 the first auction was held for placing the new type of bonds – federal bonds with variable coupon, with maturity of more than a year and coupon disbursement, defined by weighted average yield. The year of 1996 was marked by the foundation of the first independent clearing house by MICEX in collaboration with large-size banks and regional currency exchanges. The MICEX Clearing House is a non-banking credit institution, intended for clearing and settlement of accounts of bond market participants by results of trading. The functions of a depository were also separated from the stock exchange with the creation of National Depository Centre – the biggest depository until now, to provide depository services on the market in order to improve exchange infrastructure and to adjust it to provisions of the new legislation.

The global recession of 1998, which started with the Asian financial crisis in July 1997, exacerbated Russia's financial crisis. Given the ensuing decline in world commodity prices, countries heavily dependent on the export of raw materials, such as oil, were among those most severely hit. The sharp decline in the price of oil had severe consequences for Russia. However, the primary cause of the Russian crisis was not the fall of oil prices directly, but the result of non-payment of taxes by the energy and manufacturing industries (Henry and Nixon, 1998). The interest rate for government bills was hiked up to prevent the flight of capital from Russia and to keep the exchange rate of the ruble within a narrow band, so the interest payments appeared to be much higher than the state budget income. Foreign investment rushed out of the country, and the ensuing financial crisis triggered an unprecedented flight of capital from Russia. On August 17, 1998, Russia was forced by an escalating payments crisis to devalue the ruble dramatically, declared its intention to restructure all official domestic currency debt obligations by the end of 1999 and imposed a 90 day moratorium on the repayment of private external debt, to aid its commercial banks. Russian inflation in 1998 reached 84 percent. Many banks, including some of the biggest in the country, went bankrupt.

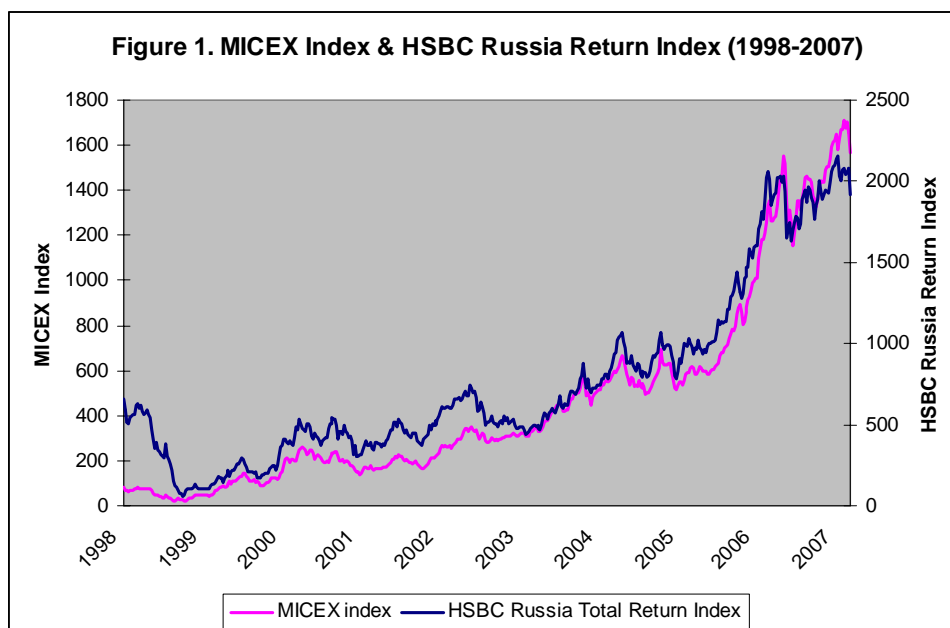
The financial crisis of 1998 had a disastrous effect on the Russian stock market. After 17 August 1998, the average daily turnover decreased several times. Most of the stock indices dropped to

historically lowest levels. HSBC Russia Return Index fell to its absolute minimum of 59,61 in September 1998.

Despite the pessimistic expectations, in 1999 and 2000 Russian stock market showed rapid growth, caused by improving macroeconomic indicators and growing commodity prices. In these two years MICEX Index rose by 195% and HSBC Russia Return Index – by 210%. The year of 2000 was marked by the development of the corporate bonds market. The initial offerings of corporate bonds were aimed at implementing the national program of attracting investments in the manufacturing sector. An important stage in the development of this segment of the securities market was the beginning of placement of banks' bonds. In 2000, the placement of bonds of a number of large Russian banks and financial companies took place on MICEX.

After 2000 the securities market continued to grow, both in terms of trading volume, number of participants and traded instruments. Thus, in 2001 the repo operations were launched, in May 2002, for the first time after the crisis of 1998, derivative instruments on stock assets were traded. In March 2004 the bank deposits with Bank of Russia were first traded in the MICEX electronic trading system. In October 2006 they were complemented by Bank of Russia's collateral loans.

The impressive Russian stock market dynamics after the crisis in August 1998 can be seen on Figure 1.



## ***2.2. Italian stock market***

Aldo Ravelli, a famous Italian investor, once defined the Italian stock market as a “pozzanghera”, the Italian word for puddle (Tamburini, 1996). Such a definition originates because of several peculiarities which had characterized this particular market for a long time. They were: a limited number of listed companies, the lack of institutional investors, the presence of hidden funds within the firms, a reduced presence of foreign investors and the pervasive influence of a strong centre of power which was represented by Mediobanca. The latter was a merchant bank that used to play an essential role in all of the main financial events after the Second World War, whose importance is nowadays fading away contemporaneously to the increasing importance of the Italian stock exchange.

In fact, given the objective delay in the start of the process of industrialization, the Italian “German-type” mixed banks were the primary source of finances for the Italian firms, especially for the companies involved in heavy industries, such as weapons or cars. On the other hand, another typical trait of the structure of the Italian industry, e.g. the extremely high concentration of medium and small firms contributes to explain the scarce development of the Italian stock market with respect to the economies of comparable countries. Obviously, because of the higher costs of producing accurate information for the market, small companies prefer to rely on a bank to fulfil their financial needs. For example, a research of the same Mediobanca analyzing the balance sheet of the Italian firms, documented that the ratio of shareholders' equity over the total liabilities was even declining from an average value of 28% in 1968 to a minimum of 14.9% in 1977. Within the same period Italian economy appeared to grow at an impressive rate such that in 1987 the Italian GDP had overtaken the Britain's (Economist, 2005).

Nonetheless, the situation started to improved gradually. A milestone in the path to efficiency is the law issued by the government in 1984, which allowed special asset management firms to offer mutual funds to Italian investors. Before, the investment offering firms had to be located In Luxembourg. Meanwhile, the stock index became less sensitive to internal political issues, such as the result of general elections, and more correlated with the behaviour of the other European markets.

The capitalization grew constantly and in 1992 ranked fourth within the European Community. However, the ratio of the market capitalisation to GDP remained at a remarkably low level of

16% against an European average between 25% and 30% (Euromoney, 1992). This evolution, even if not completely terminated, led to the privatization of the Italian stock exchange in 1998. Nowadays Borsa Italiana, namely the Italian bourse, counts more than 270 listed stocks and is based in Milan. In 2000 the capitalization represented little more than the 2% of the world capitalization (Andrea Beltratti, 2000). It has responsibilities for providing the market with liquidity, maximizing its transparency and competitiveness, while aiming at profiting from these activities. It operates by means of an electronic trading system for real-time execution in which more than 130 domestic and international brokers participate through remote memberships. This institution, mainly owned by major Italian banks, “regulates, develops and manages the Italian equities markets (MTA/MTAX and Mercato Expandi), the market for derivative instruments, the Italian Derivatives market (IDEM), the Securitised Derivatives market (SeDeX), the electronic Fixed Income market (MOT), the electronic ETFs and ETCs market (ETFplus) and the Electronic Market (MTF) where index open-end and closed-end Funds, (ETFs – Exchange-Traded Funds) are traded” (Borsa Italiana, 2007).

In turn, the Equities Market is divided in five segments, which differ in terms of market capitalization and compliance requirements, in order to be more appealing for “small caps” to raise funds directly on the equity market. Furthermore, the segmentation may help the Italian investors to diversify better their shares’ portfolios. These segments are: Blue Chip, the segment devoted to companies with a capitalisation over 1 billion euros, STAR, the segment for companies with a capitalisation of less than 1 billion euros, Standard which is the market for all companies with a capitalisation between 40 million and 1 billion euros, and Mercato Expandi which is dedicated to smaller companies with a minimum capitalization of one million euros.

The major indexes, all updated every minute, are: the Mibtel, which is a weighted average of all the shares listed, the MIB30, based on the thirty stocks with greater capitalization and the S&P, which represents the underlying trend on the market and is constructed according to specific criteria set by Standard & Poor’s. Another index of minor importance is the Midex, which refers to the most liquid listed blue-chip stocks.

To conclude, the Italian economy is also currently facing important challenges regarding the effort to enlarge the size of its firms in order to cope with the increased competition, given the ever-growing internationalization of the global economy. In case of success, this might consequently lead to a growth of the Italian stock exchange capitalization at an outstanding rate.

## **Chapter 3. The Data**

### ***3.1. Overview and sources***

We have obtained two sets of data to be plugged into the probit model – for Italian and Russian markets. The parameters required for the model include long term and short term interest rates, stock index closing values and other data including macroeconomic variables which can be applied to extend the basic model. The sources of data included Datastream, Reuters, EcoWin, databases of MICEX, Bank of Russia and Bank of Italy.

### ***3.2. Italian market data***

Due to the availability of data, the chosen time period is from January 1982 up to March 2007. As for the stock market index, MSCI Italy Total Return Index was chosen. The value of the index is calculated in euro. It includes gross dividends, which means that the series approximates the maximum possible dividend reinvestment. The amount reinvested is the dividend distributed to individuals, but does not include tax credits.

Following Liu, Resnick and Shoesmith (2004) we will try to apply the U.S. yield spread as explanatory variable. Therefore, we have collected 305 monthly observations for the three month and ten year constant maturity benchmark bonds of the U.S. Treasury, starting from January 1982 up to March 2007.

Additionally, we collected 230 observations of the three month constant maturity benchmark bill for the Italian market, from February 1988 to March 2007. The yield is calculated in euro. This data provides a necessary complement to calculate the return of the market timing strategy. Moreover, the yield of the Italian T-bill will be employed as risk free rate to calculate the excess monthly return of the index return and the market timing strategy return. The descriptive statistics of the data is shown in Table 1.

**Table 1. Data Descriptive Statistics (Italian Market)**

Series	Mean	Median	Standard deviation	Skewness	Kurtosis
MSCI Italy Total Return Index	1535.48	1076.82	1114.18	0.68	-0.77
U.S. yield spread, %	1.73	1.71	1.16	-0.11	-1.10
3-month benchmark T-bill, %	6.81	5.17	4.27	0.46	-1.17

### 3.3. Russian market data

According to certain peculiarities of the Russian stock market, e.g. it is an emerging market which appeared in the beginning of 90s and started to develop after the crash in August 1998, when the government appeared to be insolvent for its bond obligations, the bond data that we use includes 3 year benchmark bond first launched in June 2001 and 1 month interbank euro deposit rate. It is worth noticing that it would have been obviously wrong to use specific traded bonds because their yields will be changing due to decreasing time to maturity. As the total return index we are using the HSBC Russia Return Index calculated by HSBC bank in euro on a daily basis. Additionally, we gathered the data for EMBI+ Russia Index, which measures the yield spread between the U.S. and Russian treasury bonds. For Russian market we collected monthly and weekly data described above, comprising 114 and 497 observations correspondingly. The short length of the sample with monthly observations may be a problem for estimating a trustworthy model. In that case only weekly data will be applied. In addition, the Russian stock market is very correlated with the oil prices which can also be used in the model as an independent variable. Thus we gathered a series of the Russian oil (Urals) prices for the whole period. Besides, some macroeconomic fundamental data was collected, namely the consumer price index – CPI. The descriptive statistics of the weekly data is given in Table 2.

**Table 2. Data Descriptive Statistics (Russian Market)**

Series	Mean	Median	Standard deviation	Skewness	Kurtosis
National yield spread, %	2.58	2.62	2.88	-0.57	3.99
HSBC Russia Return Index	753.37	584.10	525.77	1.19	0.55
EMBI+ Russia Index	1092.60	542.80	1459.45	2.06	3.26
Urals oil price, \$	30.49	26.64	15.36	0.86	-0.19
CPI Index	148.91	148.19	37.88	-0.01	-1.17



## Chapter 4. Methodology

### 4.1. The probit models theory<sup>1</sup>

The probit model is a particular type of binary response model. In the binary response model the dependent variable is a “limited dependent variable”, e.g. it is varying only within a specific range of values. Specifically, it can assume the value of either one or zero. Formally, this can be written as:

$$P(y = 1 | x) = G(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k) = G(\beta_0 + x\beta), \quad (1)$$

where  $G$  is a nonlinear function taking on values strictly between zero and one:  $0 < G(z) < 1$ , for all real numbers  $Z$ .

In the particular case of the probit model,  $G$  is the standard normal cumulative distribution function, which can be expressed by the following formula:

$$G(z) = \Phi(z) \equiv \int_{-\infty}^z \phi(v) dv \quad (2)$$

$$\phi(z) = (2\pi)^{-1/2} \cdot \exp(-z^2 / 2) \quad (3)$$

where  $\phi(z)$  is the standard normal density function, which implies that the  $P(y = 1 | x)$  has to be strictly between zero and one for all values of the parameters and the  $x_j$ . It is worth noticing that both (1) and (2) are increasing functions.

The normality assumption which characterizes the probit model is what makes this method very common in econometrics, also because of the several nice properties of the normal distribution.

The binary response models can be derived from an underlying “latent variable model”. Let  $y^*$  be an unobserved, or latent variable, determined by:

$$y^* = \beta_0 + x\beta + e, \quad y = 1[y^* > 0], \quad (4)$$

where we introduce the notation  $I[.]$  to define a binary outcome. The function  $I[.]$  is called the indicator function, which takes on the value one if the event in brackets is true, and zero otherwise. Therefore,  $y$  is one if  $y^* > 0$  and  $y$  is zero if  $y^* \leq 0$ . We assume that  $e$  is independent of

---

<sup>1</sup> Sections 4.1 and 4.2 give a summary of Chapter 17.1. in Woolridge (2003).

$x$  and that  $e$  is the specific binary response function, which in the case of the probit model is the standard distribution function.

From (4) and the assumptions given, we can derive the response probability for  $y$ :

$$P(y = 1 | x) = P(y^* > 0 | x) = P[e > -(\beta_0 + x\beta) | x] = 1 - G[-(\beta_0 + x\beta)] = G(\beta_0 + x\beta), \quad (5)$$

which is equivalent to (1).

In most applications of binary response models the primary goal is to explain the effects of the  $x_j$  on the response probability  $P(y = 1 | x)$ . The “direction” of the effect of  $x_j$  on  $E(y^* | x) = \beta_0 + x\beta$  and on  $E(y | x) = P(y = 1 | x) = G(\beta_0 + x\beta)$  is always the same. However, the latent variable  $y^*$  rarely has a specific unit of measurement. Thus, contrary to the traditional linear model, the magnitude of each coefficients are not, by themselves, especially useful.

Given the nonlinear nature of  $G(\cdot)$ , to compute the partial effect of roughly continuous variable on  $P(x) = P(y=1|x)$  we must obtain the partial derivatives:

$$\frac{\partial p(x)}{\partial x_j} = g(\beta_0 + x\beta)\beta_j, \quad (6)$$

where  $g(z) \equiv \frac{dG}{dz}(z)$ .

Since  $G$  is the cumulative distribution function of a continuous random variable,  $g$  is a probability density function. In the probit cases,  $G(\cdot)$  is strictly increasing which entails that  $g(z) > 0$  for all  $z$ . Hence, the partial effect of  $x_j$  on  $p(x)$  depends on  $x$  through the positive quantity  $g(\beta_0 + x\beta)$  which means that the partial effect always has the same sign as  $\beta_j$ .

## ***4.2. Maximum likelihood estimation of probit models***

Given the nonlinear nature of  $E(y|x)$ , “OLS” and “WLS” methods are not applicable. Because maximum likelihood estimation is based on the distribution of  $y$  given  $x$ , the heteroskedasticity in  $Var(y|x)$  is automatically accounted for.

Assume that we have a random sample of size  $n$ . To obtain the maximum likelihood estimator, conditional on the explanatory variables, we need the density of  $y_i$  given  $x_i$ . We can write this as:

$$f(y | x_i; \beta) = [G(x_i\beta)]^y [1 - G(x_i\beta)]^{1-y}, y = 0,1, \quad (7)$$

where, for simplicity, we absorb the intercept into the vector  $x_i$ . We can easily see that when  $y=1$  we get  $G(x_i\beta)$  and when  $y=0$  we get  $1 - G(x_i\beta)$ . The log-likelihood function for observation  $i$  is a function of the parameters and the data  $(x_i, y_i)$  and is obtained by taking the log of (7)

$$\ell_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)]. \quad (8)$$

Since  $G(\cdot)$  is strictly between zero and one,  $\ell_i(\beta)$  is defined for all values of  $\beta$ . The log-likelihood for a sample size of  $n$  is obtained by summing (8) across all observations

$\Lambda(\beta) = \sum_{i=1}^n \ell_i(\beta)$ . The MLE of  $\beta$  maximizes this log-likelihood. Because of the nonlinear nature

of the maximization problem, we cannot write a formula for the probit maximum likelihood estimates. Even though, the use of MLE can raise a relevant amount of problems, under very general conditions, the MLE is consistent, asymptotically normal and asymptotically efficient. Each coefficient is provided with the correspondent standard error, which can be used to perform  $t$ -test and build confidence intervals.

### 4.3. Goodness-of-fit tests for probit models<sup>1</sup>

#### 4.3.1. The Hosmer-Lemeshow test

The data is grouped into  $j = 1, 2, \dots, J$  groups, and let  $n_j$  be the number of observations in group  $j$ . We define the number of  $y_i = 1$  dependent observations and the average of predicted values in group  $j$  as:

$$\begin{aligned} y(j) &= \sum_{i \in j} y_i \\ \bar{p}(j) &= \sum_{i \in j} p_i / n_j = \sum_{i \in j} (1 - F(-x_i'\beta)) / n_j \end{aligned} \quad (9)$$

The Hosmer-Lemeshow test statistic is computed as:

$$HL = \sum_{j=1}^J \frac{(y(j) - n_j \cdot \bar{p}(j))^2}{n_j \cdot \bar{p}(j) \cdot (1 - \bar{p}(j))} \quad (10)$$

---

<sup>1</sup> This section is based on the EViews 5.0 technical notes.

The distribution of the *HL* statistic is not known. However, Hosmer and Lemeshow (1989, p.141) report evidence from extensive simulation indicating that when the model is correctly specified, the distribution of the statistic is well approximated by a  $\chi^2$  distribution with  $J - 2$  degrees of freedom. These findings are based on a simulation where  $J$  is close to  $n$ .

#### 4.3.2. The Andrews test

The data be grouped into  $j = 1, 2, \dots, J$  groups. Since  $y$  is binary, there are  $2J$  cells into which any observation can fall. Andrews (1988) compares the  $2J$  vector of the actual number of observations in each cell to those predicted from the model, forms a quadratic form, and shows that the quadratic form has an asymptotic  $\chi^2$  distribution if the model is specified correctly.

EViews manual gives the following brief description of the test. Let  $A$  be an  $n \times J$  matrix with element  $a_{ij} = 1 \cdot (i \in j) - p_i$ , where the indicator function  $1 \cdot (i \in j)$  takes the value of one if observation  $i$  belongs to group  $j$  with  $y_i = 1$ , and zero otherwise (the columns for the groups with  $y = 0$  should be dropped to avoid singularity). Let  $B$  be the  $n \times K$  matrix of the contributions to the score  $\partial l(\beta) / \partial \beta'$ . The Andrews test statistic is  $n$  times the  $R^2$  from regressing a constant (one) on each column of  $A$  and  $B$ . Under the null hypothesis that the model is correctly specified,  $n \cdot R^2$  is asymptotically distributed  $\chi^2$  with  $J$  degrees of freedom.

#### 4.4. The probit model to forecast bear market

We are using the yield-curve spread as explanatory variable to forecast a bear stock market. The model in the work of Resnick and Shoesmith (2002) looks as follows:

$$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 SPREAD_t), \quad (11)$$

where

$P$  is the probability forecast of a bear stock market  $k$  months later; Resnick and Shoesmith (2002) choose  $k = 1$ ,

$F$  is the cumulative normal probability density function,

$R_t$  is a binary variable which equals to 1 if the stock market in time  $t$  is currently in a bear market of at least 6 months in duration, otherwise,  $R_t = 0$ . Thus, a bear market in this model is defined as a consecutive decrease of the stock market index in the following six month period.

$SPREAD_t$  is the yield spread between the 10 year benchmark bond and 3 month T-bill.

This model gives for every period an ex ante estimate of the probability that the market is going to be a bear market, which can be then used to adopt a certain market-timing investment strategy of choosing between investments in the stock market or the short-term government bonds.

#### ***4.5. Model extensions***

We are carrying out modified (as compared to the model of Resnick and Shoesmith, 2002) models estimated by changing the definition of a bear market, e.g. one or two months of consecutive decrease of the stock market index, instead of six, thus changing the dependent binary variable. However, the authors define it as six months of decreasing prices in their model and use 40 years of monthly data, but we are restricted in terms of data for both Italian and Russian market (discussed in Chapter 3), that is why we are forced to use shorter bear market horizon to obtain a reliable forecast. As we mentioned earlier, lack of observations especially for Russian market can be a problem when estimating a significant probit model.

That is the reason why we decided to switch to weekly data in estimating the model for the Russian index. However, even if we are aware that this procedure will yield more noisy coefficient, this could be proved to be useful especially when considered that emerging markets are subject to a higher level of volatility. Consequently, the binary dependent variable should also be redefined to be several weeks of consecutive decrease of the market index. For the Italian market we will apply monthly data because 305 observations seem to be enough for probit model estimation and forecasting. However, as compared to the model by Resnick and Shoesmith (2002) who define a bear market as six months of consecutive decrease, this period should be reduced for the Italian market since the it is growing constantly during the period we chose and a six month bear market will not yield a reasonable forecast.

We attempt also to add or change the explanatory variable. For Italy we apply the U.S. yield spread, since it has already been proved by Liu, Resnick and Shoesmith (2004) that it is useful for timing many established markets. On the other hand, since we do not find much literature documenting the empirical correlation between Russian and U.S. stock markets, we do not apply the U.S. yield spread to forecast the probability of downturn of the market.

For the Russian stock market we investigate if the spread between the domestic bonds and U.S. treasuries is significant in predicting the Russian stock market movements. It is measured by EMBI+ Russia index, which was introduced by JP Morgan to provide a benchmark index to track emerging markets debt and is calculated on a daily basis using the yields of Russian eurobonds. The index shows the risk premium for the emerging markets due to higher volatility, political instability and it is a measure clearly related to the fundamentals of the economies of emerging countries.

Another option is to add the current stock index value at time  $t$ , which may have an effect on the forecast of market behavior in the next periods. Some basic macroeconomic variables such as oil price or consumer price index or monetary policy indicators such as refinancing rate can also be tested for significance.

Therefore, due to the differences in time periods of the data we use, and different factors that have effect on the emerging and developed stock market behaviour, we are forced to use different explanatory variables and different definitions of a bear market in probit models for Russian and Italian markets.

#### ***4.6. Forecasting***

Considering that the model should give us the probability of the bear stock market in a certain period of time, we should test the model for reliability by comparing the forecasted probabilities and the actual stock market performance. The best possible model should demonstrate an increase in forecasted probability straight before the actual downturn of the market. To obtain these probabilities we apply the out-of-sample forecasting because this technique allow to overcome the over-fitting problem, if one takes place. In fact, the in-sample analysis may be improved by simply adding more regressors to the model. On the other hand, testing the out-of-sample performance of the model is likely to show how a parsimonious model provide more precise signals to time the market.

The model estimation and forecasting is carried out in EViews 5 using probit binary estimation method with Quadratic Hill Climbing optimization. The forecasting is based on the regression run for the estimation sample and uses the same coefficients for the whole forecasted sample. As estimation window we are choosing a series of at least 60 first observations. Then we carried out

the out-of-sample forecasting, first by forecasting a bear market 1 period ahead consecutively with the same estimation window, until a bear market of at least two periods in duration occurred. Then we reestimated the model by adding the previously forecasted observations to the estimation period and ran forecasting again until a new bear market period happened. In this way, the data provided forecasts of bear markets up to April 2007.

The result is a series of forecasted probabilities of a bear market, which can be directly compared on the same graph with actual stock market index performance. After trying different explanatory variables and different definitions of the binary variable, the most effective model will be chosen.

Following the model by Resnick and Shoesmith (2002) then we chose filtering probabilities which determine the investor's behavior on the market. A probability screen implies that, given a probability of a bear market lower than the screen, the funds will be invested into stocks. As soon as the forecasted probability goes higher than the screen, an investor exits the stock market and invests into domestic short-term bills. As Estrella and Mishkin (1998) and Liu, Resnick and Shoesmith (2004) stated in their works with the probit model, we can expect low probability screens to work well given that within the estimation windows the market is growing. Vice versa, in case of declining share prices, since we are evaluating the probability of bear market, we would have expected the opposite.

#### ***4.7. Market timing testing***

Empirical evidence documenting superior market timing returns has to be thoroughly analyzed because of the strong implications this would have for the financial theory, e.g. the violation of the Efficient Market Hypothesis, as well as for the general equilibrium in the security market. The works of Fama (1972), and Treynor and Black (1973) contributed to classify the skills which can be used to provide an investment with better characteristics in terms of risk and return into two main categories: stock picking skills, which refer to the movement of one stock relative to the others, and market timing skills, which predict the general movements of the index compared to the bonds.

Clearly, our analysis aims at identifying superior market timing strategies. In this perspective, Henriksson and Merton (1981) developed a useful framework to analyze the so-called

“Macroforecasting skills”, namely the ability to successfully time the market. Their model requires the assumption that either the securities are priced according to the CAPM or a multifactor return structure. Under this assumptions, we can use least-squares estimator to run the following regression:

$$R_{pt} - R_{ft} = \beta_{0p} + \beta_{1p}Y_{1t} + \beta_{2p}Y_{2t} + \varepsilon_{pt}, \quad (12)$$

where

$R_{pt}$  is the return on the probit market-timing portfolio in time period  $t$ ,

$R_{ft}$  is the risk-free rate of return,

$Y_{1t} = \max(0, R_{mt} - R_{ft})$ , with  $R_{mt}$  representing return on the market portfolio,

$Y_{2t} = \min(0, R_{mt} - R_{ft})$ ,

$\varepsilon_{pt}$  is the residual error term.

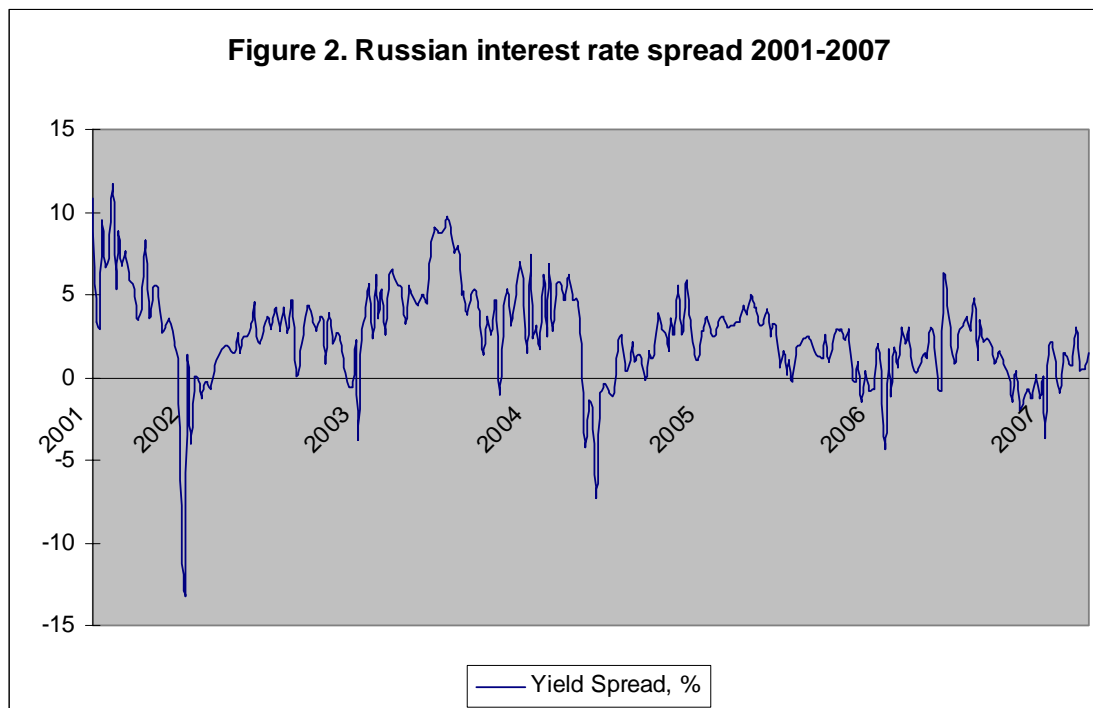
The risk-free asset is represented by the domestic short-term T-bill yield and the market portfolio – by the total return stock index. In this equation excess returns on a portfolio  $p$  are regressed on the bull market risk premium  $Y_{1t}$  and the bear market risk premium  $Y_{2t}$  to estimate the portfolio’s sensitivity to up and down movements of the market. Successful market-timing requires that  $(\beta_{1p} - \beta_{2p}) > 0$ . In addition, we will compute the Sharpe ratios to analyze the reward-to-variability of each strategy.



## Chapter 5. Russian Stock Market Timing

### 5.1. Basic model estimation

As discussed earlier, given the lack of data for the Russian stock market, we switch to weekly data covering the period from August 1997 up to March 2007. That yielded 497 observations, which is enough to build a reliable model. Given the shorter intervals of data, the binary dependent variable has to be redefined. Thus, given that the Russian stock market is much more volatile, we change the binary variable to be two weeks of consecutive decrease of the HSBC stock index. To build the basic model, as described by Resnick and Shoesmith (2002), we obtain the spread between a 3-year government benchmark bond and 1-month deposit rate. It was possible to obtain the spread for the period from June 2001, when the 3-year benchmark bond was first published, up to April 2007. The spread dynamics is shown in Figure 2.



In the graph above we can notice the remarkable degree of volatility which characterizes the spread. This can be related to the higher risk connected with the Russian economy. However, such a variability could impede the proper use of the spread as explanatory variable in the probit model, which would likely originate too noisy forecasts.

Then, the model estimation period was chosen – from June 2001 to the end of 2002, comprising 81 observations. The following probit model is obtained using maximum likelihood estimation method for forecasting the probability of a bear market during 2003-2007:

$$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 SPREAD_t), \quad (13)$$

where

$P$  is the probability forecast of a bear stock market one week ahead,

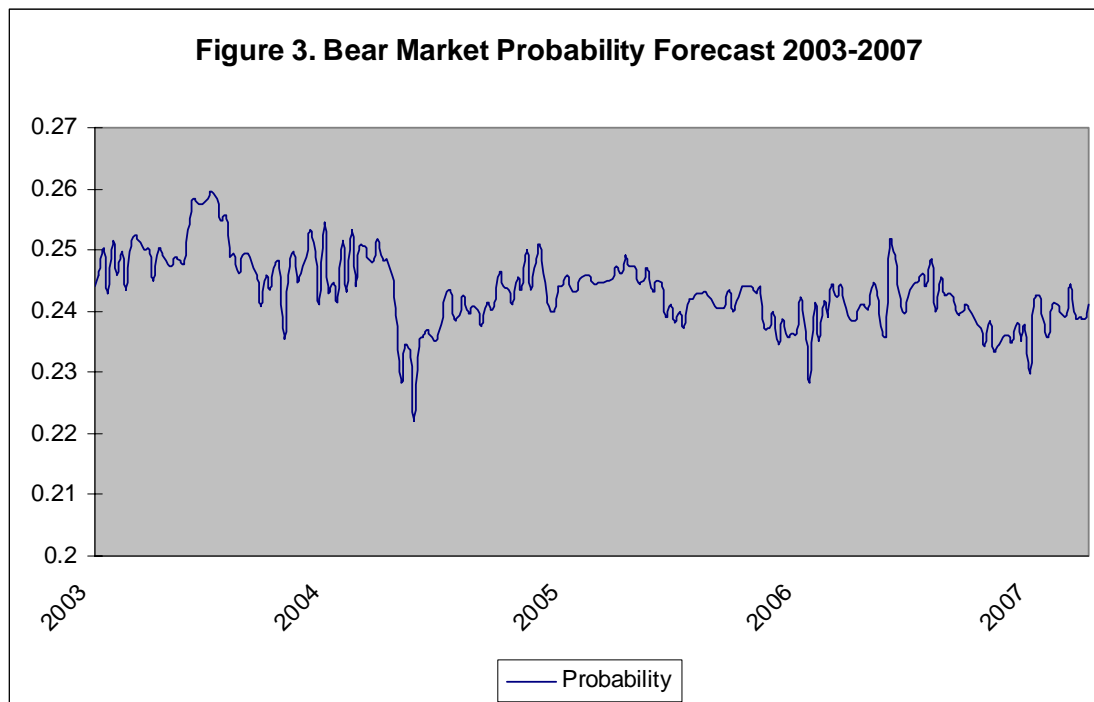
$F$  is the cumulative normal probability density function,

$R_t$  is a binary variable which equals to 1 if the stock market in time  $t$  is currently in a bear market of at least two weeks in duration, otherwise  $R_t = 0$ ,

$SPREAD_t$  is the yield spread between the 3-year government benchmark bond yield and 1-month interbank deposit rate.

However, the spread variable appears to be highly insignificant in this model with a  $p$ -value of 0.8671 in the significance test.

The graph of forecasted bear market probability is given in Figure 3.



As it can be noticed, the graph does not demonstrate a clear pattern of a bear market probability distribution varying between 22% and 26%. At the same time there were significant shifts and shocks in Russian economy, which resulted in several sharp falls and upturns of the stock index. Banking crisis in summer 2004 and bankruptcy of oil giant Yukos in 2006 followed by a drop in stock index can be an example, which is not reflected on the probability graph. The stock index dynamics was shown in Figure 1. Therefore, considering also the insignificance of the spread variable in this model as well as peculiarities of the Russian stock market, we are forced to somehow modify this basic model proposed by Resnick and Shoesmith (2002).

## ***5.2. Introducing country risk premium***

First of all, after several trials and errors, we came to a conclusion that the spread between domestic and foreign interest rates, particularly the U.S., is more significant and gives a clearer picture, than the spread between domestic rates with different time to maturity. This spread is reflected, for instance, in EMBI+ Russia index published by JP Morgan on a daily basis. In fact, the index measures the risk premium for an emerging stock market as compared to the established one. The significant impact which the country risk premium has on returns in emerging stock markets was discussed in the following research papers.

Domowitz, Glen and Madhavan (1998) divide the emerging market risk premium into two major components – currency risk premium, related to adverse movements in the exchange rate and country risk premium which represents the risk that the government might default on its obligations. Government borrowings are a significant source of capital for development in emerging countries, and debt instruments often carry significant premia over their counterpart equivalents in more mature markets such as the U.S. Thus, the term structure of currency and country risks may contain important information about investors' beliefs about future economic events. The relation between currency and country risk and returns in financial markets is an important issue. Investors will revise their beliefs regarding future currency and country risks following price movements in the debt and equity markets. Alternatively, changes in risk premia may anticipate future volatility in these markets, or common factors may affect both risk premia and market volatility. As concluded by Domowitz, Glen and Madhavan (1998), the magnitudes of the estimated country and currency risk premia indicate that governments in emerging markets can significantly reduce domestic interest rates if they can improve international perceptions of the risk of possible currency devaluations and government default. Ferson and Harvey (1991)

also found that exposure to financial and macroeconomic risks can forecast stock returns, which can be attributed to the presence of time-varying risk premiums that are imperfectly reflected in realized returns.

Baek, Bandopadhyaya and Du (2005) examine the determinants of market-assessed sovereign risk, measured by the Brady bond stripped yield spread. They found that liquidity, solvency and economic stability variables significantly affect the market premium of country risk. However, according to the conclusion they make, in the emerging economies the market's attitude towards risk plays an even greater role in the determination of the country risk premium. Countries that are not necessarily experiencing changes in economic fundamentals may find changes in their bond yield spreads because of a change in the market's attitude towards risk. However, the market's attitude towards risk does not affect published country risk ratings, which are based primarily on the economic fundamentals of the rated countries. According to the authors, this explains why often there is a divergence between published country risk premium ratings and market-assessed country risk premium measures like the Brady bond yield spread.

To sum up, the strong relationship between macroeconomic variables and country risk premium can justify the use of the latter to forecast the correspondent emerging stock market return, analogously to the yield spread.

### ***5.3. The role of oil prices***

Using merely EMBI+ index gave us an obviously wrong probability forecast, which did not reflect the actual stock market movements. Thus, it was decided to extend the probit model by adding other economic determinants, which may prove to be significant. It is well-known that the Russian economy and its stock market has been tied for the last few years with the ever-increasing oil prices. Therefore, adding oil price as an explanatory variable can contribute to making a consistent bear market forecast. We will provide now some academic background to justify our choice.

There are a number of published research papers examining the relationship between the oil prices and stock market returns. Most of the research has focused on the developed countries. The paper by Chen, Roll, and Ross (1986) is one of the first papers to systematically investigate the impact of macroeconomic innovations on stock price returns. They found that interest rates,

inflation rates, bond yield spreads, and industrial production have risk that is priced in the stock market. They did not, however, find any evidence that oil price risk is rewarded by the stock market. Further research, for example by Ferson and Harvey (1995) finds evidence that an oil price risk factor does have a statistically significant but different impact on the 18 equity markets that they study.

Jones and Kaul (1996) use quarterly data to test whether the reaction of international stock markets (Canada, Japan, United Kingdom, and the United States) to oil shocks can be justified by current and future changes in real cash flows and changes in expected returns. Using the Producer Price Index for Fuels as a measure of oil prices, they do find a relationship between oil prices and stock market returns. After including future industrial production into the analysis, however, they find that the reaction of Canadian and U.S. stock prices to oil price shocks can be completely accounted for by the impact of these shocks on real cash flows.

Huang et al. (1996) focus on the relationship between daily oil futures returns and daily U.S. stock returns. Using a vector autoregression (VAR) approach, they find that oil futures returns do lead some individual oil company stock returns but oil futures returns do not have a strong impact on broad based market indices like the S&P 500.

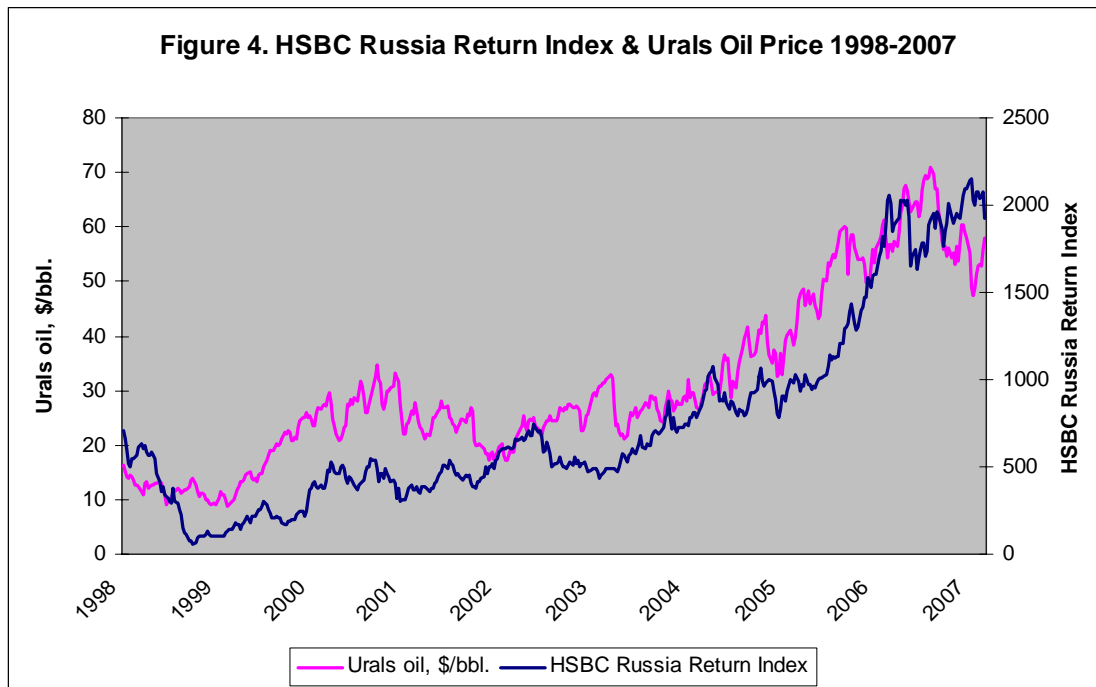
Sadorsky (1999) estimates a vector autoregression model with monthly data to study the relationship between oil prices changes and real stock returns in the U.S. In his analysis he finds that oil price changes and oil price volatility both play important roles in affecting real stock returns. There is evidence that oil price volatility shocks have asymmetric effects on the economy. In particular, positive oil price shocks have a greater impact on stock returns and economic activity than negative oil price shocks.

In contrast to the work done on developed markets, relatively little research has focused on the relationship between energy prices and stock markets in emerging countries. Recent work in this area includes the article by Papapetrou (2001). He uses a multivariate vector autoregression model to study the dynamic interaction between oil prices, real stock prices, interest rates, and real economic activity in Greece. His empirical results show that changes in oil prices influence real activity and employment.

The natural resource sector in general and the oil and energy sectors in particular have a more important role in Russia than in most countries. Oil and energy resources are among Russia's main exports and domestic supplies are critical for the whole economy (Rautava, 2002). The oil industry provides a considerable share of state budget revenue and convertible currency earnings. The share of oil is about 31% in total primary energy production, and about 50% in primary energy exports. It is estimated that the oil sector is responsible for about 20% of the total revenue of the state budget and 40% of total earnings from exports (Cukrowski, 2004). Moreover, many countries of the former Soviet Union depend on supplies of Russian oil for their fuel and energy needs, which gives Russia a special position in the region. Although the development of the oil industry may affect the whole Russian economy and its stock market in the next several years, oil, like all other energy sectors in Russia, faces a number of problems, including low domestic prices, a poor regulatory framework, little competition and underinvestment.

The interdependence of Russian oil price and HSBC Russia total return index can be seen in Figure 4.

To conclude, it is rational to assume that adding an independent variable representing the price of Russian oil – Urals, will contribute to the model and increase its forecasting power.



#### 5.4. Estimation of the final model

The probit model for Russia is defined as:

$$P(R_{t+1} = 1) = F(\alpha_0 + \alpha_1 \cdot EMBI_t + \alpha_2 \cdot OP_t), \quad (14)$$

where

$P$  is the probability forecast of a bear stock market 1 week ahead,

$F$  is the cumulative normal probability density function,

$R_t$  is a binary variable which equals to 1 if the stock market in time  $t$  is currently in a bear market of at least 2 weeks in duration, otherwise,  $R_t = 0$ ,

$EMBI_t$  is the EMBI+ Russia index averaged on a weekly basis,

$OP_t$  is the Urals oil price averaged on a weekly basis.

As the initial estimation window from now on we choose the three year period 1997-1999. It covers both the stock market growth in 1997, default in August 1998, and its consecutive recovery period in 1999. The estimation period comprises 125 weekly observations. Then we carry out the out-of-sample forecasting with re-estimating the model every time a bear a market of at least two weeks in duration occurs (for details see section 4.6). The relationship between the probability and stock market index is shown in Figure 5.



The graph demonstrates a negative relationship between the forecasted bear market probability and the stock index with a few exceptions. First of all, this probit model cannot account for political events or events which do not have a direct effect on oil prices or country risk premium. Thus, the stock index decline in June 2006 with the bankruptcy of the oil corporation Yukos is accompanied by the probability decrease, which is obviously wrong. Secondly, the sharp probability fall in the end of 2005 is mostly caused by reestimation of the model parameters in December 2005 together with a quick soaring of the index during 2006.

## 5.5. Model testing

### 5.5.1. Testing the coefficient significance

Table 3 provides the test statistics for the  $\alpha_1$  and  $\alpha_2$  coefficients of the probit model. As the number of re-estimations of the model appeared to be huge, we give the coefficient values on annual basis.

**Table 3. Significance of  $\alpha_1$  and  $\alpha_2$  coefficients**

Estimation range	$\alpha_1 \cdot EMBI$	$\alpha_2 \cdot OP$
1997–1999	-2.91**	-2.08**
1997–2000	-2.85**	-1.42
1997–2001	-2.42**	-1.36
1997–2002	-2.53**	-1.81*
1997–2003	-2.00**	-1.68*
1997–2004	-1.86*	-1.55
1997–2005	-2.01**	-2.51**
1997–2006	-1.41	-2.66**

\* Significant in a two-tailed test at the 10 percent level

\*\* Significant in a two-tailed test at the 5 percent level

Examination of Table 3 shows that EMBI+ index is highly significant in almost all years, whether oil prices sometimes demonstrated a  $p$ -value of about 15-25% in a two-tailed significance test. In spite of that, as it was mentioned before, taking out oil prices from the model means omitting an important explanatory variable and that gives a poor result. Lagging the oil price did not yield better outcome.



### 5.5.2. Goodness-of-fit tests

The Hosmer-Lemeshow test and Andrews test were applied in EViews for the probit model in order to check for goodness of fit. The results are shown in Table 4.

**Table 4. The Hosmer-Lemeshow and Andrews tests**

<b>Estimation range</b>	<b><i>HL</i></b>	<b><i>Andrews</i></b>
1997–1999	9.28*	21.94
1997–2000	7.91*	12.80*
1997–2001	14.91*	19.71
1997–2002	10.04*	13.42*
1997–2003	9.10*	10.02*
1997–2004	11.17*	11.52*
1997–2005	8.87*	12.05*
1997–2006	4.46*	5.65*

\* The model is correctly specified at the 5 percent level

The values given in the table are Hosmer-Lemeshow and Andrews test statistics,  $\chi^2$  distributed with 10 and 8 degrees of freedom respectively. The test methodology is described in section 4.3. Both tests show correct probit model specification in almost all periods.

### 5.6. Market timing returns

Based on these results we studied the viability of using the probit model to time the stock market and beat a stock-only buy-and-hold strategy by forecasting a bear stock market one week in advance. Thus we obtained a series of weekly forecasted probabilities for 2000-2007. Then we constructed series of weekly returns on the stock market by taking the percentage increase in the index value in one week. We also got returns on the short-term bills by transforming the annual yield into weekly.

Three probability screens were used: 25%, 30% and 35%, which implies that once the probability of a bear market is above the screen, the investor exits the stock market and invests into short-term treasury bills. The choice of probabilities is explained in section 4.6. Moreover, it seems logical considering the data statistics with median probability of 28.7% and standard deviation of 7.7 percentage points.

Basing on this method, we obtained a series of weekly market timing strategy returns which should be compared to the stock market returns, which correspond to a buy-and-hold strategy. Using the series we calculated the monthly and annual compound return on the market timing strategy for the whole forecasting period 2000-2007. Then we calculated it separately for the period of modest market growth alternating with sharp declines of 2000-2002 (can be seen on Figure 1), the period of the fastest growth in 2003-2004 and the period of modest growth in 2006-2007. The results are presented in Table 5.

**Table 5. Economic Performance of Market Timing Strategy**

Compound return	Buy-and-hold strategy	Market timing strategy		
		P>25%	P>30%	P>35%
<b>A. January 2000 - April 2007</b>				
Monthly, %	2.15%	1.40%	2.19%	2.02%
Annual, %	25.81%	16.79%	26.29%	24.20%
<b>B. January 2000 - December 2002</b>				
Monthly, %	0.78%	0.93%	2.83%	1.89%
Annual, %	9.34%	11.15%	33.94%	22.62%
<b>C. January 2003 - December 2005</b>				
Monthly, %	4.08%	1.89%	1.91%	2.41%
Annual, %	48.96%	22.73%	22.88%	28.91%
<b>D. January 2006 - April 2007</b>				
Monthly, %	1.39%	1.39%	1.39%	1.39%
Annual, %	16.65%	16.65%	16.65%	16.65%

As it can be noticed, the highest gain from timing the market comes from the first period of 2000-2002 at all probability levels. This means that the probability of a bear market forecasted for this period could have been effectively used by switching between stocks and T-bills in the right time, thus retaining a annual return which is higher than the buy-and-hold stock return by 1.8, 24.6 and 13.3 percentage points for 25%, 30% and 35% probability levels respectively. This fact can be explained by a highly unstable and modestly growing stock market in that period primarily due to very volatile prices of oil. However, a high emerging market risk premium determined a high return on government borrowings, particularly because the economy was still recovering from the crisis of 1998.

On the contrary, the sky soaring of the market in 2003-2005 made the market timing ineffective. The consequences of the crisis were overcome, and the risk free rates started to decline, while the stock market became more attractive to national and international investors and pushed up

the buy-and-hold returns. In the third period the probability of a recession dropped below the 25% level due to ever-increasing oil prices and country risk premium decline. Thus, the market timing strategy at all probability levels suggests holding the stocks during current growth period.

Considering the total return for the whole period, market timing proves to be profitable at 30% probability screen, giving a 0.5% higher annual return.

### 5.7. Market timing testing

The Henriksson-Merton (1981) parametric model was applied to determine whether the probit model is capable of producing statistically significant market timing results. For the description of the model see section 4.7.

The results for three market timing strategies are presented in Table 6.

**Table 6. Market Timing Testing**

	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_1-\beta_2$	$R^2$
<b>1) P&gt;25%</b>					
Coefficient	0.0016	0.1432	0.2304	<b>-0.0872</b>	0.1911
Standard error	(0.0016)	(0.0372)*	(0.0368)*		
<b>2) P&gt;30%</b>					
Coefficient	-0.0007	0.5286	0.4719	<b>0.0567</b>	0.7571
Standard error	(0.0018)	(0.0409)*	(0.0406)*		
<b>3) P&gt;35%</b>					
Coefficient	-0.0003	0.7787	0.7362	<b>0.0425</b>	0.5002
Standard error	(0.0477)	(0.0473)*	(0.0021)*		

\* Significant in a two-tailed test at the 1 percent level

We found that for the second and third strategies the “up-market” betas is higher than the “down-market”, indicating that these market timing strategies were effective. The difference between the “up-market” and “down-market” betas,  $\beta_1-\beta_2$ , which is an indicator of market timing ability, appears to be the highest for the strategy with 30% probability screen. All betas appear to be statistically significant at the one percent level, however the  $R^2$  is low for the ineffective first strategy, but it is the highest for the most profitable, the second strategy.

The Reward-to-variability analysis, namely the Sharpe ratio for the excess returns on different strategies, is given in Table 7.

**Table 7. Reward-to-Variability Analysis**

Measure	Buy-and-hold strategy	Market timing strategy		
		P>25%	P>30%	P>35%
Mean excess return	0.1565%	0.0141%	0.1646%	0.1322%
Standard deviation	5.28%	2.29%	3.74%	4.60%
Sharpe ratio	2.96%	0.62%	4.40%	2.87%

These results confirm that the most effective strategy in terms of return and risk is the second market timing strategy with 30% probability screen, which exhibits the highest Sharpe ratio of 4.40%.

## **Chapter 6. Italian Stock Market Timing**

As previously stated, the main purpose of our analysis with respect to the Italian market is to attempt an application of the probit market timing strategy as described by Resnick and Shoesmith (2002).

### ***6.1. Dependent binary variable choice***

The first step to carry out any probit model is the definition of the binary variable. If we were to follow Resnick and Shoesmith (2002), we would define it as at least 6 months of consecutive decreases in the market. However, given our series of returns, such a procedure is absolutely not feasible, since between February 1982 and April 2007, we do not observe 6 months of consecutive decreases. In other words, the binary variable would not show any variability, which entails the absolute impossibility to run any regressions.

Therefore, we opt for reducing the required number of months necessary to define a bear market. With respect to this matter, we should point out that there are not clear theoretical reasons for supporting the definition used by Resnick and Shoesmith (2002), which is employed merely because the normal duration of a recession is at least 6 months. However, even though the stock prices are clearly affected by the business cycle, it does not seem reasonable to assume such a strict correspondence between the dynamics of the GDP and the stock index. For example, the expectation of the investor about the recession could become assimilated in the share prices faster than the actual duration of the recession, as in the case of a sudden drop in the stock index. In our perspective, an argument against this idea is represented by the so called “stock market volatility puzzle”, which refers to the observation that the volatility of real stock market returns can not be fully explained by the variability of the underlying fundamentals of the economy.

After running the regression against the U.S. yield spread with different definitions of the dependent binary variable (from two to four months of consecutive decrease) we do not observe any relevant difference in the general pattern of the forecasted probability. More specifically, the shape of the graph is the same; what is changing is the average value of the forecasted probability of market downturn, which is obviously greater for shorter interval. Hence, we

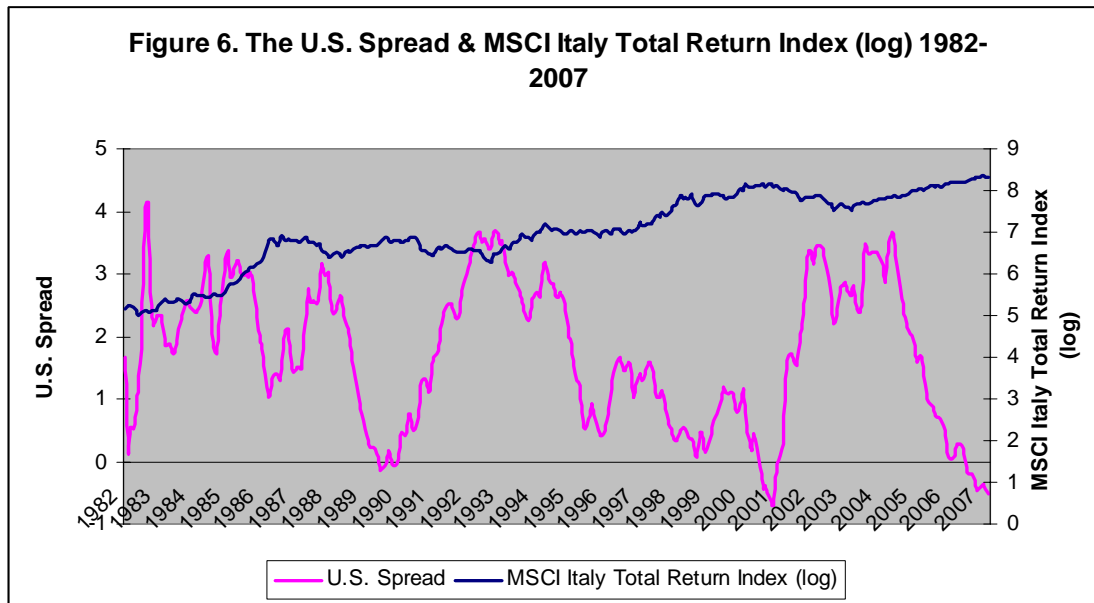
choose our final model to have a binary variable defined as two consecutive months of decrease in the stock market.

## ***6.2. The U.S. spread as explanatory variable***

To proceed with our analysis, we choose as explanatory variable the U.S. yield spread. As mentioned earlier, most of the arguments supporting such a choice were discussed by Liu, Resnick and Shoesmith (2004) for other similar established markets. In particular, the Italian stock market, as any other European established market, is likely to be strongly affected by the dynamics of the U.S. economy, by means of a twofold connection: directly by the expectations of the investors and indirectly through the macroeconomic interrelationships between Italy and U.S. In fact, it is not infrequent to read in financial newspapers the U.S economy to be called as the “locomotive of the world growth”.

Furthermore, a study of Morgan Stanley and Co. found that “Share prices were correlated with the movement of the dollar against the local currency in each of seven European markets” (International Herald Tribune, 1995). In particular the Italian shares had one of the greatest correlations, with a coefficient which was estimated as 0.8. Given that the relative strength of the dollar is related to the U.S. macroeconomic fundamentals, such phenomenon implies that good news for the U.S. economy will be likely to affect positively the return on the Italian stock market. The positive correlations between dollar and the Italian stock market held for a long time. While we should be aware of the constantly changing nature of relationship among financial variables, which can also be varying according to the different stages in the business cycle, this link is still likely to be relevant. This empirical evidence pinpoints the importance of identifying the turning point in the U.S. economy to manage effectively the market timing strategies on European markets.

The relationship between the U.S. yield spread and the logarithmic Italian stock market index can be seen on Figure 6. The cross-correlation at one lag between the two series is 0,38.



On the graph we can notice some salient characteristics of particular concern. First of all, when considering this time period, every time the yield spread reaches a level greater than 3, we observe a “turning point” in the trend on the stock market. More specifically, if we were to buy shares each time the yield spread were above 3 and sell them when the yield became negative, this could have certainly yield a better return than the buy-and-hold strategy. Furthermore, between two “turning points”, the series shows clearly a negative correlation. Therefore, we consider extremely important to estimate the parameters of our regression for homogeneous period in terms of stage of the business cycle. Following this method, since a flat yield is generally considered as a fairly reliable indicator of recession in the future, we can assume that an entire business cycle takes place within the interval of time between the two points in which the yield spread equals zero.

### ***6.3. Estimation of the final model***

With respect to inclusion of additional explanatory variables, we found by numerous trials that a parsimonious model worked best. For instance, when we tried to add some measure of stock market return as an independent variable, even though the estimated coefficient was highly significant, the forecasted probability which resulted out of such regression was excessively volatile to provide a clear signal to be used in the framework of out-of-sample forecasting. Having chosen the U.S. yield spread as the only explanatory variable, we obtained the following probit model:

$$P(R_{t+k} = 1) = F(\alpha_0 + \alpha_1 SPREAD_t), \quad (15)$$

where

$P$  is the probability forecast of a bear stock market 1 month later,

$F$  is the cumulative normal probability density function,

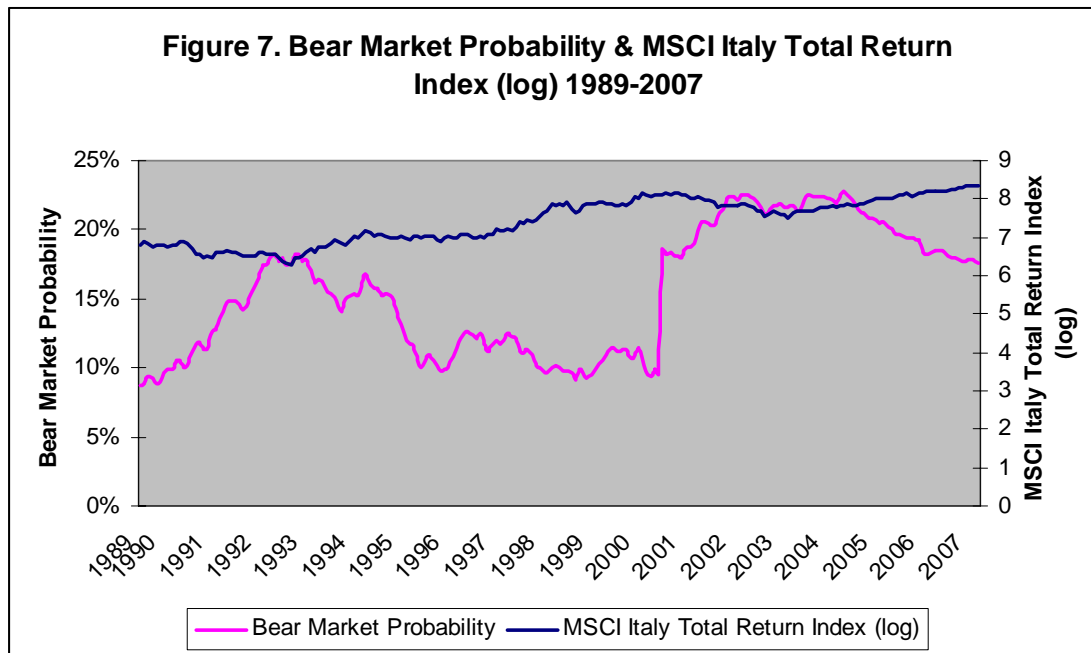
$R_t$  is a binary variable which equals to 1 if the stock market in time  $t$  is currently in a bear market of at least two months in duration, otherwise,  $R_t = 0$ ,

$SPREAD_t$  is the yield spread between the 10 year U.S. Treasury bonds and 3 month T-bills.

As specified earlier, we divide the sample period into four sub-intervals by choosing three points in time which we assume to be turning points in the business cycle, as reflected in the slope of the yield curve. More specifically, when the yield spread equals zero we re-estimate the coefficients including all the data up to date. We should emphasize that such a procedure is the only reasonable alternative to the method of Resnick and Shoesmith (2002) who were re-estimating the regression at each point in time characterized by a bear market, defined as 6 months of decrease in the stock index. In fact, in our case it is not feasible given the endless number of regression we would have had to run manually. On the other hand, estimating the regression at predefined interval of time regardless the stage of the business cycle, say every year, would clearly yield a biased result.

Thus, starting from May 1982 and using all the data until June 1989, we forecast the bear market probability until June 2000. At this point, since the yield curve is flat, we re-estimate the parameters. The procedure is repeated another time since also in June 2006 the spread is equal to zero. The relationship between the logarithm of MSCI Italy Total Return Index and bear market probability for a comparable period of time is demonstrated on Figure 7.





The sudden jump in the probability which took place before 2001 is primarily determined by the fact that the yield spread decrease sharply within the same time period. As shown on the graph, the probability of downturn in the market remains fairly low in absolute value for the whole period.

## 6.4. Model testing

### 6.4.1. Testing the coefficient significance

The significance of the estimated coefficient is shown in Table 8.

**Table 8. Significance of  $\alpha_1$  coefficient**

Estimation	$\alpha_1$ * SPREAD
April 1982–June 1989	0.58
April 1982–June 2000	0.42
April 1982–June 2006	0.35

Unfortunately, none of the coefficients of the U.S. yield spread in the regression are significant. This could be partially due to the length of our sample as well as to the certain characteristics of this particular time period. Specifically, some previous research suggests that the predicting

power of the yield curve was reduced during the 80s and the beginning of the 90s, in particular the spread failed to predict the recession of 1990-91 (Haubrich and Dombrosky, 1996 and Dotsey, 1998), which represents our initial estimation window. In other words, a failure in predicting recession, given the relationship between economic performance and share prices, could consequently lead to a biased estimation. In fact, the significance of the coefficient is clearly increasing with the length of the sample.

#### 6.4.2. Goodness-of-fit tests

The Hosmer-Lemeshow test and Andrews test were applied in EViews for the probit model in order to check for goodness of fit (see section 4.3 for details). The results are presented in the following table.

**Table 9. The Hosmer-Lemeshow and Andrews tests**

<b>Estimation range</b>	<b><i>HL</i></b>	<b><i>Andrews</i></b>
April 1982 – June 1989	5.62*	20.24
April 1982–June 2000	13.11*	21.02
April 1982–June 2006	11.67*	14.58*

\* The model is correctly specified at the 5 percent level

Table 9 shows the outcomes of the Hosmer-Lemeshow and Andrews tests, where the test statistics are  $\chi^2$  distributed with 10 and 8 degrees of freedom respectively. While the Hosmer-Lemeshow test seems to confirm the goodness-of-fit of the model, the Andrews test offers a positive result just for the last regression. However, as for the case of the significance of the coefficients, the goodness-of-fit appears to improve with the increase in the length of the sample.

#### 6.5. Market timing returns

The following table shows the result of the market timing strategy for the different periods taken into account.

**Table 10. Economic Performance of Market Timing Strategy**

Compound Return	Buy-and-hold strategy	Market timing strategy	
		P>10%	P>20%
<b>A. June 1989 - March 2007</b>			
Monthly, %	0.75%	0.65%	0.82%
Annual, %	8.99%	7.82%	9.80%
<b>B. June 1989 - June 2000</b>			
Monthly, %	1.06%	0.92%	1.06%
Annual, %	12.77%	10.98%	12.77%
<b>C. July 2000 - June 2006</b>			
Monthly, %	0.11%	0.24%	0.30%
Annual, %	1.36%	2.87%	3.61%
<b>D. July 2006 - March 2007</b>			
Monthly, %	1.54%	0.26%	1.54%
Annual, %	18.48%	3.16%	18.48%

As we can see, choosing a filter probability of 20% yields a return which dominates the other two strategies for each of the four time periods. In particular, this strategy has the same return of the buy-and-hold strategy for period B and D. The strategy which is derived from choosing a filter equal to 10% is always dominated in terms of return by the other two apart from period C, in which the 10% buy-and-hold strategy performed worse than the others.

To sum up, the strategy with 20% probability filter offers a better result in terms of both return and risk than the buy-and-hold. The lower risk is justified by the fact that the short term Italian bill has a lower variance than the share prices.

### **6.6. Market timing testing**

As described in section 4.7, we must proceed by analyzing the returns of the market timing investment strategy by applying a rigorous framework. The first step involves running the regression defined by the work of Henriksson and Merton (1981). The results are given in Table 11.

**Table 11. Market Timing Testing**

	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_1-\beta_2$	$R^2$
<b>1) P&gt;10%</b>					
Coefficient	-0.0006	0.2026	0.1549	<b>0.0477</b>	0.1824
Standard error	(0.0027)	(0.0461)*	(0.0562)*		
<b>2) P&gt;20%</b>					
Coefficient	-0.0061	0.9672	0.6848	<b>0.2824</b>	0.8545
Standard error	(0.0025)	(0.0418)*	(0.0510)*		

\* Significant in a two-tailed test at the 1 percent level

The results of the regression strongly confirm the market timing ability of our model for both probit strategies. However, for the strategy with 20% filtering probability the result is even stronger because of the higher difference between “up” and “down” market sensitivities, which is intended to assess the market timing strategy. Moreover, we can notice that this strategy shows a fairly high R squared, which is a common measure of goodness-of-fit. Both the regression coefficients result to be very significant. Next, by computing the Sharpe ratio, which is commonly used in finance to compare risk and return of different investments, we can gain better insight of the performance of the market index with respect to the market timing strategy.

**Table 12. Reward-to-Variability Analysis**

Measure	Buy-and-hold strategy	Market timing strategy	
		P>10%	P>20%
Mean excess return	0.17%	0.09%	0.24%
Standard deviation	6.41%	2.74%	5.89%
Sharpe ratio	2.72%	3.16%	4.03%

The table above displays that the strategy characterized by a filtering probability of 20% dominates the other two in terms of reward to variability. Of particular interest, the market timing strategy defined by a screen probability of 10% is still offers a greater reward to variability than the buy and hold strategy. By looking at the figures, we can easily notice that this result is mainly due to the level of volatility of the returns of this investment strategy, which is distinctly lower than the other two standard deviations. Overall, we find evidence of significant “macro-forecasting” power of our probit model.

## Conclusions

The results of our research appear to reinforce the importance of using probit modelling to successfully time the Russian and Italian stock markets. Though we used two different sets of explanatory variables for each country, the rationale behind the two models was identical: we wanted to observe whether the informational content of financial spreads closely related to the dynamics of the business cycle could be employed to construct better portfolios compared to the benchmark of the buy-and-hold strategy.

With respect to our study of the Italian market, building on the work of Liu, Resnick and Shoemith (2004), we found that the U.S. yield spread seems a viable predictor of downturn also on the Italian market. In fact, despite a low significance of the coefficients in the regressions, both our market timing strategies exhibit a greater Sharpe ratio relative to the buy-and-hold strategy. Furthermore, the Henriksson and Merton (1981) test corroborates the evidence of the market timing power of our probit model.

On the other hand, the analysis of the Russian market demonstrates the potential relevance of country risk premium in explaining the volatility of the stock market, even if the past literature does not provide significant empirical evidence on this issue. Using the oil price as an explanatory variable in this case, which has already been proved reasonable in several researches for oil-dependent developing countries, also works well for Russia. Market timing manages to outperform the buy-and-hold strategy in terms of return and risk for a screen probability of 30%, yielding a 0.5% higher average annual return and a lower variance. During the most unstable period in the Russian economy – 2000-2002, switching between stocks and bonds according to the 30% strategy could yield a return 3.6 times higher than from buying and holding the stocks. However, we should point out that the short length of the sample period in addition to the more noisy character of the weekly observations force to be cautious in interpreting the results. However, we should point out that the short length of the sample period in addition to the more noisy character of the weekly observations force to be cautious in interpreting the results.

As in the Italian case, the ex-post market timing test confirms the profitability of our strategy with a screen probability of 20%, which provides the Italian investor with a 0.81% higher average annual return and a higher Sharpe ratio as compared to the buy-and-hold strategy. The

10% market timing strategy works better than the buy-and-hold during 2000-2006, and also has a higher Sharpe ratio.

Furthermore, even if we use different sample periods for Russia and Italy, the Sharpe ratios have comparable values. This could be also due to the fact that the Italian stock index was more volatile in the 80s than recently.

However, several limits could have biased our analysis. First of all, the short length of the sample, especially the period of 10 years in the Russian case, could represent a serious drawback in our study. In fact, the significance level of the U.S. spread coefficient in the probit model for the Italian market appears to improve with the length of the sample. Second, when we calculated the return of the market timing strategy, we did not account for the transaction costs which the investors will bear in order to switch from the stock to the bond market and vice versa. Moreover, we should not underestimate the importance of unexpected events not reflected in the value of the yield spread or the country risk premium and, thus, not affecting the forecasted bear market probabilities. However, such events may seriously change the behavior of the stock index. Finally, we cannot rule out the possibility of having omitted some potentially important variables which might have improved the out-of-sample forecasting power of the model. The limited amount of time we had did not permit to carry out a comprehensive analysis for many other variables which could appear to be useful in out-of-sample forecasting.

In particular, future research should focus on the testing of other variables such as the yield spread change, which could indicate the change in the monetary policy, or the advantage of using the EMU yield spread in addition to the U.S. spread. Lagging one or more explanatory variables can also prove to be fruitful.

In addition, the behavior of the stock index can also be predicted by forecasting the bull market probability. The same models may be applied, however the definition of the dependent binary variable should be changed to be several periods of consecutive index increases. In this case the investor will exit the stock market once the bull market probability drops below a certain critical level and invest into T-bills, and vice versa.

It will also be interesting to see, whether our models can work for other established and developing markets because the study of Liu, Resnick and Shoesmith (2004) covers only nine most developed countries.

To conclude, despite the possible shortcomings of the research, our study corroborates the empirical evidence that the yield spread contains important information to forecast the stock market. If this is true, the puzzle is to understand how that can be explained by the financial theory.

## References

1. Ahrens R., 2002, Predicting recessions with interest rate spreads: a multicountry regime-switching analysis, *Journal of International Money and Finance*, Vol. 21, Issue 4.
2. Andrews, Donald W., 1988, Chi-square diagnostic tests for econometric models: Introduction and applications, *Journal of Econometrics*, Elsevier, Vol. 37(1), 135-156.
3. Anonymous, 1995, Study Ties Bourses to Dollar's Fluctuations, *International herald tribune*.
4. Anonymous, 2005, *The Economist*, Survey: Addio Dolce Vita.
5. Anonymous, 2007, La borsa italiana e gli intermediari finanziari secondo Giorgio Tagli, Seminar of May 2007 at the department of Economics of the University "Federico Primo" di Napoli.
6. Baek, Bandothyaya and Du, 2005, *Journal of International Money and Finance*, No. 24, 533-548.
7. Beltratti A., 2000, "Capire la Borsa", *Edizioni Il Sole24ore*.
8. Borsa Italiana, report 2007.
9. Campbell, 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-400.
10. Chen, Roll and Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.
11. Cukrowski, J., 2004, Russian Oil: The Role of the Sector in Russia's Economy, *Post-Communist Economies*, Vol. 16, No. 3, September 2004.
12. Domowitz, I., Glen J., Madhavan A., 1998, *The Journal of Financial and Quantitative Analysis*, Vol. 33, No. 2. (Jun., 1998), 189-216.
13. Dotsey M., 1998, The predictive content of the interest rate term spread for future economic growth, *Economic Quarterly – Federal Reserve Bank of Richmond*, Vol. 84, Issue 3, 31-51.
14. Duarte, Venetis and Paya 2005, Predicting real growth and the probability of recession in the Euro area using the yield spread, *International Journal of Forecasting*, Vol. 21, 261–277.
15. Dueker, 1997, Strengthening the case for the yield curve as predictor of economic recession, *Federal Reserve Bank of Saint Louis*, Vol. 79.



16. Estrella and Mishkin, 1996, The yield curve as a predictor of U.S. recessions, Federal Reserve Bank of New York, *Current Issues in Economics and Finance*, No. 2, 1-6.
17. Estrella and Mishkin, 1998, Predicting U.S. recessions: Financial variables as leading indicators, *Review of Economics and Statistics* 80, 45-61.
18. Fabio Moneta, 2005, Does the Yield Spread Predict, Recessions in the Euro Area?, *International Finance* 8:2, pp. 263–301
19. Fama, E. 1972. Components of investment performance. *Journal of Finance* 27, no. 25, 51-67.
20. Federico, G., 1996, “Italy, 1860-1940: A Little-Known Success Story”, *The Economic History Review*, New Series, Vol. 49, No. 4, 764-786.
21. Ferson, W., and C. Harvey, 1991, The Variation of Economic Risk Premiums, *Journal of Political Economy*, No. 99, 385-415.
22. Fisher and Palasvirta, 1990, High Road to a global marketplace: The transmission of international market fluctuations, *Financial Review* 25, 371-394.
23. Gerlach J., 2005 Imperfect Information and Stock Market Volatility, *The Financial Review*, Volume 40, Issue 2, 173-194.
24. Hamilton, 1989, A new approach to the economic analysis of non-stationary time series and the business cycle, *Econometrica*, Vol. 57, No. 2. (Mar., 1989), 357-384.
25. Harvey, 1989, Forecasts of economic growth from the bond and stock markets, *Financial Analysts Journal*, 38-45.
26. Haubrich and Dombrosky, 1996, Predicting Real Growth Using the Yield Curve Economic Review, *Federal Reserve Bank of Cleveland*, Vol. 32 Issue 1, 26-36.
27. Henriksson, Roy D. and Robert C. Merton, 1981, On Market Timing and Investment Performance: Statistical Procedures for Evaluating Forecasting Skills, *Journal of Business*, Vol. 54, No. 4 (October), 513-533.
28. Henry, B. and Nixon, J., 1998, The Crisis in Russia: Some Initial Observations, *Economic Outlook*, Vol. 23, No. 1, November 1998.
29. Hosmer D. and Lemeshow S., 1989, *Applied Logistic Regression*, John Wiley & Sons, Inc.
30. Huang, R., Masulis, R. and Stoll, H., 1996. Energy shocks and financial markets. *Journal of Futures Markets*, No. 16, 1–27.
31. Jones, C. and Kaul, G., 1996, Oil and the stock markets, *Journal of Finance*, No. 51, 463–491.

32. Kawaller I., Koch P. and Koch T., 1987, The Temporal Price Relationship Between S&P 500 Futures and the S&P 500 Index, *The Journal of Finance*, Vol. 42, Issue 5, 1309-1330.
33. Lin, Engle and Ito, 1994, Do bulls and bears move across borders? International transmission of stock returns and volatility, *Review of Financial Studies*, No. 7, 507-538.
34. Liu, Resnick B. and G. Shoesmith, 2004, Market Timing of International Stock Markets Using the Yield Spread, *The Journal of Financial Research*, Vol. XXVII, No.3, 373-391.
35. Moneta F., 2005, Does the Yield Spread Predict Recessions in the Euro Area?, *International Finance* 8:2, 263–301.
36. Moscow Interbank Currency Exchange, history report 2005.
37. Neely, 2001, International interest rates linkages, Federal Reserve Bank of St. Louis, *International Economic Trends*, August 1st.
38. Papapetrou, E., 2001, Oil price shocks, stock markets, economic activity and employment in Greece, *Energy Economics*, No. 23, 511–532.
39. Rautava, J., 2002, The Role of Oil Prices and the Real Exchange Rate in Russia's Economy, *Bank of Finland, BOFIT Discussion Papers*, no. 3, 2002.
40. Resnick B. and G. Shoesmith, 2002, Using the Yield Curve to Time the Stock Market, *Financial Analysts Journal*, 82-90.
41. Sadorsky, P., 1999, Oil price shocks and stock market activity, *Energy Economics*, No. 21, 449–469.
42. Scarsi, Pio, 1992, Guide to European Equity Markets, 1992, Italy. *Euromoney*, pg. 34.
43. Siegel J., 1998, Stock for the Long Run, 2<sup>nd</sup> edition New York: McGraw-Hill.
44. Study Ties Bourses to Dollar's Fluctuations, *International herald tribune*, 1995.
45. Tamburini, 1996, Misteri d'Italia: Aldo Ravelli Il re mida della borsa, *Edizioni Milano*.
46. Templeman, Santoro, 1982, The Italian Economy, *Journal of Economic Literature*, Vol. 20, No. 1, pp. 107-108.
47. Treynor J., Black F., 1973, How To Use Security Analysis To Improve Portfolio Selection, *The Journal of Business*, Vol. 46, Issue 1, 66.
48. Woolridge, J., 2003, Introductory Econometrics: A Modern Approach, Thomson: South-Western, 553-561.
49. Yang J. and Bessler D., 2004, The International Price Transmission In Stock Index Futures Markets, *Economic Inquiry*, Vol. 42, Issue 3, 370-386.