Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

MASTER THESIS

Gambling in Stock Markets: Empirical Evidence from Europe

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Abstract

Motivated by the recent evidence of investors' preference for stocks with lottery-type payoffs documented on the U.S. stock markets, I investigate preferences for stocks that appear to be like lotteries in Europe. Across 14 markets, lottery-type stocks, characterized by high idiosyncratic skewness, high idiosyncratic volatility and low price, underperform and exhibit a *"lottery premium"*. Furthermore, preferences for lottery-type stocks can help to explain the puzzling negative relation between past idiosyncratic volatility and returns, which does not persist after controlling for past extreme positive returns. Examining the relation between national revenues from gambling and *"lottery premium"* I find that countries featuring higher gambling revenues also exhibit a higher *"lottery premium"*. Overall, the results indicate that lottery preferences might impact investment decisions and stock prices.

JEL Classification	G11, G12
Keywords	gambling, lottery-type stocks, idiosyncratic volatility, maximum returns

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Abstrakt

Práce je motivována nedávným výzkumem amerických akciových trhů, který ukazuje, že investoři preferují akcie s loterijními výnosy. Na datech z Evropských trhů zkoumám preference pro akcie, které se chovají podobně jako loterie. Napříč 14 Evropskými trhy jsou loterijní akcie, charakterizované vysokou idiosynkratickou šikmostí, vysokou idiosynkratickou volatilitou a nízkými cenami, nadhodnocené a vykazují *"loterijní prémii"*. Preference pro loterijní akcie navíc může vysvětlit anomálii v negativním vztahu mezi idiosynkratickou volatilitou a budoucimi výnosy. Zkoumáním vztahu mezi příjmy z hazardu a *"loterijní prémií"* ukazuji, že země s vyššími příjmy z hazardu mají také vyšší *"loterijní prémie"*. Tyto výsledky naznačují, že loterijní preference mohou mít vliv na investiční rozhodování a ceny ackií.

Klasifikace JEL	G11, G12
Klíčová slova	hazard, loterijní akcie, idiosynkratická volatilita, maximální výnosy

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The author declares that the work has not been used to fulfill the requirements of another degree program.

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Helsinki, May 18, 2012

Signature

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Master Thesis Proposal

Author	Bc. Petra Vokatá
Supervisor	Jiří Novák, Ph.D.
Proposed topic	Gambling in Stock Markets: Empirical Evidence from Europe

Topic characteristics This thesis will focus on preference for stocks with lottery characteristics. The mainstream financial theory based on mean-variance framework describes investors as rational and risk averse. However, we can observe gambling behavior on stock markets as well, as in state lotteries. The aim of this thesis is to show that in addition to risk aversion we can also find risk-seeking behavior on stock markets. Empirical analysis will help to describe why, how, where and when investors gamble on stock markets.

Evidence of human attitude toward gambling can be traced back to primitive pre-historic societies. There are many psychological and socioeconomic factors that determine our propensity to risk and gamble. Unrealistic optimism about own returns, aspirations of higher than actual wealth, hope and aversion to fear and regret are some of the factors than can explain irrational risk taking in lotteries. Friedman and Savage (1948) offered one explanation to the lottery puzzle: even if people know what the risk is, they might take it to distinguish themselves; it can be the only way for them to improve their economic status.

Scandinavian countries offer a good opportunity to study stock gambling because it is the region with one of the highest lottery sales as a percentage of GDP in Europe. While on average the lottery sales count for 0.55% of GDP in European countries, in Finland they count for more than 0.8% and in Sweden 0.796% of GDP (Garrett 2001). Although in Norway and Denmark the percentage is lower, it is still slightly higher than the average. The stock

markets in Nordic countries are developed and they seem to provide a sufficient number of listed companies for empirical research.

Hypotheses

1. There is a positive lottery premium on lottery-type stocks.
2. The lottery premium is higher during the periods of market downturns.
3. Gambling on stock markets and in state lotteries are positively correlated across countries.

Methodology In the first part of the thesis, motivation to gamble will be described using the behavioral approach. The literature review will cover findings from previous researches and introduce the theoretical concepts related to the topic. Definitions of gambling and lottery premium as well as an empirical definition of lottery-type stock will be discussed as the basis for further empirical analysis. To define the lottery-type stock I will follow Kumar (2009) who uses three main characteristics: very low prices relative to the highest potential payoff, extremely high variance and positively skewed payoffs. In other words he describes these stocks as cheap, very risky with extremely small probability of a huge reward and very high probability of a small loss. To examine the premium which gambling investors assign to lottery-type stocks, I will use the Fama and MacBeth (1973) cross-sectional regression method with additional lottery factor. I will test separately the significance of all three lottery characteristics and their influence on investors. Monthly stock prices from Copenhagen SE, Helsinki SE, Oslo SE and Stockholm SE will be used. Time series model will be used to estimate the correlation between lottery preferences and economic factors. Differences between countries and relation to gambling in state lotteries will be examined using cross-sectional regression. Additional econometric methods will be used to correct Fama-MacBeth standard errors for potential serial correlation. To ensure that the regression estimates are robust, additional robustness checks will be conducted.

Outline

1. Introduction
2. Gambling on Stock Markets
3. Testable Hypotheses

4. Empirical Analysis
5. Conclusion

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Author

Supervisor

Chapter 1

Introduction

Gambling dates back to the era of cavemen and can be observed in nearly all societies (Hacking 2006). For centuries people have gambled in lotteries despite the well-known fact that lotteries have a negative expected return. Today's global lottery market, accounting for more than $200 billion, clearly indicates that gambling still occurs regardless of the higher level of people's literacy. This risk-seeking behavior constitutes a challenge to conventional assumptions on human behavior underlying much of the financial theory. Shefrin & Statman (2000) offer an explanation arguing that people keep different "mental accounts" with different risk attitudes. Specifically, people segregate their portfolios to two mental accounts, one designed to avoid poverty and another, associated with risk-seeking behavior, to aspire for higher wealth.

Moreover, recent literature shows that risk-seeking behavior is not restricted to the demand for lotteries where the stakes are typically moderate and non-financial emotional benefits such as the thrill of the game can plausibly explain the observed phenomenon. Even in the context of capital markets where investors are expected to be rational, they seem to reveal preference for stocks with lottery-type payoffs, i.e. cheap and very risky assets with tiny probability of extreme positive return (Kumar 2009; Kumar *et al.* 2011a;b; Doran *et al.* 2011). To empirically define these lottery-type stocks Kumar (2009) uses three lottery characteristics: low price, high positive skewness and high idiosyncratic volatility. Using data from U.S. stock markets he shows that these stocks underperform and investors gain lower returns from their lottery investments.

Perhaps the most interesting application of preferences for lottery-type stocks is that they offer possible explanation for the so-called *"iv puzzle"*, an anomalous negative relation between lagged idiosyncratic volatility and future

returns documented by Ang *et al.* (2006; 2009). The observed phenomenon is puzzling because stocks with higher unsystematic risk show lower returns contrary to the theoretical predictions. Specifically, under full diversification only systematic risk should be priced in stock returns and not fully diversified risk averse investors should require higher returns for stocks with higher idiosyncratic risk. The anomaly, however, does not persist after controlling for maximum daily return from the past month, a characteristic used by Bali *et al.* (2011) to proxy for stocks that appear to be like lotteries.

Motivated by the findings of recent research I investigate whether stocks with lottery characteristics also exhibit a similar behavior in European stock markets. The aim of investigating several markets is to use inter-country heterogeneity in the average national preferences for gambling to infer if the similar preferences underlie the underperformance of lottery-type stocks in capital markets of individual countries. First, following Kumar (2009) I test whether lottery-type stocks underperform, i.e. show *"lottery premium"*. Second, I verify whether the *"iv puzzle"* remains significant after controlling for maximum daily return from the past month. Third, I investigate whether countries with high gambling preferences also feature high lottery premium in stock markets.

Previous studies mainly use data from the U.S. market. In addition, Doran *et al.* (2011) investigate the Chinese market and Gao & Lin (2010) study gambling in the Taiwan stock market. To the best of author's knowledge, a study covering the topic on European stock markets has not yet been conducted and therefore this thesis offers a unique opportunity to verify the findings from the U.S. stock market using different data sets.

The results contribute to the empirical evidence in three areas. Firstly, I show that *"lottery premium"* occurs also in European stock markets. Secondly, I show that the *"iv puzzle"* does not persist after controlling for past maximum daily returns and can be explained by lottery preferences. The last, and perhaps most intriguing, contribution is that the preference for lottery-type stocks appears to be correlated with gaming revenues in individual countries.

The rest of this study is organized as follows. Chapter two presents review of both theoretical and empirical literature and motivation for the research. Hypotheses are defined in third section. The fourth chapter specifies the methodology and data used to measure lottery characteristics. The next three chapters describe the results from portfolio-level analysis, cross-sectional regressions and comparison with gaming revenue. Finally, the last chapter concludes the study.

Chapter 2

Motivation

2.1 Theoretical and Behavioral Background

There are several theories and explanations for risk-seeking behavior. The insurance-lottery framework of Friedman & Savage (1948) explains the typical example of people buying both insurance and lottery tickets with utility function characterized by both a concave and convex part. Authors suggest that people are aware of the risk they are taking, but they gamble because it is the only way for them to rise to upper class. Similarly Statman (2002) finds that aspirations can lead to lottery preferences especially for people whose realized wealth is lower than their aspirations and who do not have many chances to improve it.

Other psychological factors that help to clarify risky decisions are hope, fear and regret (Statman 2002). The last one leads to aversion to realize losses by not buying lottery-type stocks or by selling losing stocks. Since investors are reluctant to realize losses, they hold on to poor-performing stocks and grudge to sell it at a loss. In addition, both state lotteries and stock trading are found attractive for many people who enjoy the accompanying challenge and the feeling that they can control the game, which in reality is random.

Errors in estimations can also bias investors towards risk taking. Firstly, people tend to believe that they are above average in many areas of their lives, including investing. This phenomenon is documented by Moore *et al.* (1999), who in an investing simulation explore an overestimation of participants' both future and past investment performance. Secondly, people tend to overweight low-probability events such as winning the lottery, as is assumed by prospect theory presented by Kahneman & Tversky (1979).

Overestimation of low probabilities and lottery preference are also connected to the well-documented favorite-longshot bias, i.e. an observed phenomenon in horse betting which reveals that favorites are underbet and longshots are overbet. As a result, expected return increases with the probability of winning.

2.2 Definitions of Lottery Stocks and Gambling in Stock Markets

To address the question whether investors gamble in stock markets, we first need to define the term gambling and distinguish it from investing. Kumar *et al.* (2011a) defines *"gambling"* in stock markets as a propensity for lottery-type payoffs, i.e. extreme returns at a low cost. Holding stocks with lottery-type payoffs itself does not depict gambling behavior and is not inconsistent with the standard theory. However, preference to seek these stocks and willingness to pay for them higher prices not corresponding to the underlying risk, can be considered as gambling.

One of the most important commonly-perceived characteristics of gambling is its negative expected value. Similarly, as in state lotteries, I expect the odds to be against gamblers and the lottery-type stocks to gain lower returns. On average, gambling investors should be able to gain neither excess nor average returns on their lottery-type portfolio but are expected to underperform. I assume that gambling preferences are not only revealed by the larger proportion of an investor's share in lottery-type stocks, as documented by Kumar (2009), but also in realized lower returns on lottery investment.

Studying gambling behavior is by its nature very problematic because it is not directly observable and it does not need to be recognized even by the agents themselves. For the empirical investigation we need an empirical definition of lottery-type stocks. Kumar (2009) defines lottery-type stocks as stocks with above-median idiosyncratic volatility, above-median idiosyncratic skewness and below-median price. Alternatively, Kumar *et al.* (2011b) in the study of institutional investors use a similar definition without the price characteristic, arguing that prudent men rules keep institutional investors from the preference for very cheap stocks. Bali *et al.* (2011) use a different approach and define lottery-type stocks as stocks with past extreme positive daily returns.

2.3 Lottery Characteristics

The purpose of lottery characteristics is to help us to identify stocks that can appear to be like lotteries for investors, i.e. to have lottery-type payoffs. Similarly to state lotteries, we want to distinguish stocks that offer a cheap opportunity to gain an extreme positive return with a very small probability.

Stocks with positively-skewed returns exhibit infrequent extreme positive returns and more frequent lower negative returns. Therefore idiosyncratic skewness is a suitable characteristic of stocks with lottery-like payoffs. Among positively-skewed stocks, investors with gambling preferences are more likely to seek low-priced stocks to minimize the maximum possible loss.

The motivation of investors with gambling preferences to prefer stocks with higher idiosyncratic volatility is not so straightforward. Kumar (2009) suggests that investors might assign a higher probability of extreme positive returns to stocks with high idiosyncratic volatility. In particular, extreme positive returns on stocks with high idiosyncratic skewness and low idiosyncratic volatility may appear to be outliers. In addition, assuming that investors value upside volatility with higher weight than downside volatility, stocks with higher idiosyncratic volatility can appear to have even more skewed returns.

Bali *et al.* (2011) offer an alternative explanation. Idiosyncratic volatility is positively correlated with extreme positive returns. Therefore investors may perceive stocks with higher idiosyncratic volatility to offer higher extreme positive returns. Evidence from state lotteries and neuroscience shows that the size of a jackpot or a huge payoff attracts more attention than its low probability (Loewenstein & Elster 1992). Therefore investors with lottery preferences can be attracted to stocks with high idiosyncratic volatility.

Finally, Boyer *et al.* (2010) show that lagged idiosyncratic volatility is a good predictor for idiosyncratic skewness and therefore investors can show a preference for stocks with high idiosyncratic volatility. This is because these stocks are more likely to have higher future skewness.

Compared to state lotteries, Kumar (2009) shows that lottery-type stocks attract similar socioeconomic clienteles. In particular, young, less-educated single men with lower incomes and non-professional jobs hold a higher proportion of lottery-type stocks. Preference for lottery-type stocks is dominant among individual investors. Institutions invest disproportionally less to lottery-type stocks compared to the market portfolio.

Deriving on these findings, I assume that investors with gambling prefer-

ences are less sophisticated and simply extrapolate past extreme returns into the future. For this reason lagged values of lottery characteristics are used in further analysis. Since extreme positive returns are persistent over the following month, as shown by Bali *et al.* (2011), this assumption seems to be reasonable.

2.4 Pricing Implication and Puzzles

Several theories explore gambling preferences with respect to asset pricing and show that they can lead to overpricing of lottery-type securities. The theoretical developments of Barberis & Huang (2008) and Brunnermeier *et al.* (2007) imply that positively skewed securities can gain lower returns. Overpricing of these stocks is derived as an implication of probability weighting implied by prospect theory, according to Barberis & Huang (2008). Brunnermeier *et al.* (2007) attribute the same result to people's overestimation of positive outcomes, which increases their expected future utility.

Allowing for lottery-like preferences and investments enables us to explain asset pricing puzzles and financial phenomena that the traditional approach cannot capture. Barberis & Huang (2008) document that pricing of positively skewed securities may be relevant for the IPO puzzle and private equity premium puzzle. Both IPOs and private equities have highly positively skewed returns but are overpriced and earn a low average return. Since they are positively skewed, investors preferring lottery-like investments can value them highly and accept their lower returns.

Boyer *et al.* (2010) show that the preference for lottery-like stocks with high idiosyncratic skewness can explain the *"iv puzzle"*. Since idiosyncratic volatility is a good predictor of expected idiosyncratic skewness, the authors point out that investors can accept lower returns in exchange for high skewness. However, idiosyncratic volatility can be perceived as a lottery factor independently on idiosyncratic skewness and this can also explain its puzzling relation to expected returns.

2.5 Previous Empirical Findings

Gambling-motivated behavior in financial markets has gotten more attention in recent research, and various empirical studies have presented investors' preference for securities with lottery payoffs (Kumar 2009; Kumar *et al.* 2011a;b; Do-

ran *et al.* 2011). Using data from the U.S. stock market, Kumar (2009) shows that individual investors are biased towards cheap and very volatile stocks with positively skewed returns. These lottery-type stocks underperform and investors gain lower returns from their lottery investments.

Furthermore, Kumar (2009) and Kumar *et al.* (2011b) document that investors and stocks of companies located in areas with higher gambling propensity proxied by religious background, exhibit a stronger preference for lottery-type stocks and higher lottery premiums. This pattern is significant for both individual and institutional investors. On an aggregate level, however, institutional investors show a preference against lottery-type stocks.

Studies investigating the relationship between idiosyncratic volatility and returns present contradictory results. For example, an early study by Lehmann (1990) finds a positive relationship between idiosyncratic risk and the cross-section of returns using monthly data. On the contrary, Ang *et al.* (2006) find a significant negative relation between lagged idiosyncratic volatility and returns. This is consistent with Bali & Cakici (2008) who show the same result using lagged daily data and value-weighted portfolios. However, when applying monthly data or equally-weighted portfolios, they find no significant relation between idiosyncratic risk and the cross-section of expected returns. Bali & Cakici (2008) conclude that the negative relationship between idiosyncratic volatility and returns is sensitive to data frequency, weighting scheme, portfolio sorting and using a screen for size, price and liquidity, and is not robust with different estimation methods. Finally, the exponential GARCH model applied by Fu (2009) shows support for the positive relation.

Other papers that investigate the relationship between both idiosyncratic skewness and idiosyncratic volatility show negative relationship between returns and both variables. Ang *et al.* (2009) in a series of tests demonstrate the negative relation between idiosyncratic volatility and returns. In addition, they find a significant negative relation between skewness and returns, but the relation is not significant after controlling for idiosyncratic volatility.

Boyer *et al.* (2010) state that predicting power of lagged idiosyncratic skewness for future idiosyncratic skewness can be improved by adding other variables, like for example, idiosyncratic volatility, and therefore the results of Ang *et al.* (2009) can be underestimated. Nevertheless results of Boyer *et al.* (2010) confirm a negative relation between returns and both variables, which persists even after controlling for each other. They show that after controlling for idiosyncratic skewness the relation between returns and idiosyncratic volatility

becomes weaker but is still significantly negative.

Table 2.1: Overview of Empirical Research on Idiosyncratic Volatility and Skewness

Study	*Variable definition*	*Method*	*Result*
Lehmann (1990)	lagged IVOL1	CSR	positive
Bali & Cakici (2008)	lagged IVOL3 (monthly)	CSR	not significant
	lagged IVOL3 (daily)	CSR	negative
Bali *et al.* (2011)	lagged IVOL1	CSR	negative
	lagged 2F ISKEW	CSR	not significant
	lagged 2F SSKEW	CSR	not significant
Fu (2009)	IVOL3 (EGARCH)	CSR	positive
Harvey & Siddique (2000)	lagged 2F SSKEW	CSR	negative
Ang *et al.* (2009)	lagged IVOL3	CSR	negative
	lagged skewness	CSR	negative
Boyer *et al.* (2010)	lagged IVOL3	FF-α CSR	negative
	predicted ISKEW	FF-α CSR	negative

Notes: The table presents previous empirical findings related to lottery characteristics. IVOL3 refers to idiosyncratic volatility estimated by Fama & French (1993) three factor model, IVOL1 is idiosyncratic volatility measured by one factor CAPM, EGARCH refers to exponential GARCH, CSR to cross-sectional regression, FF-α to alpha in Fama & French (1993) model, 2-F to two factor model including excess market return and squared excess market return, ISKEW denotes idiosyncratic skewness and SSKEW, systematic skewness. Negative result denotes that the relation between the investigated variable and returns is negative.

However, the negative relation between idiosyncratic skewness and future returns also depends on the methodology employed. Bali *et al.* (2011), in their

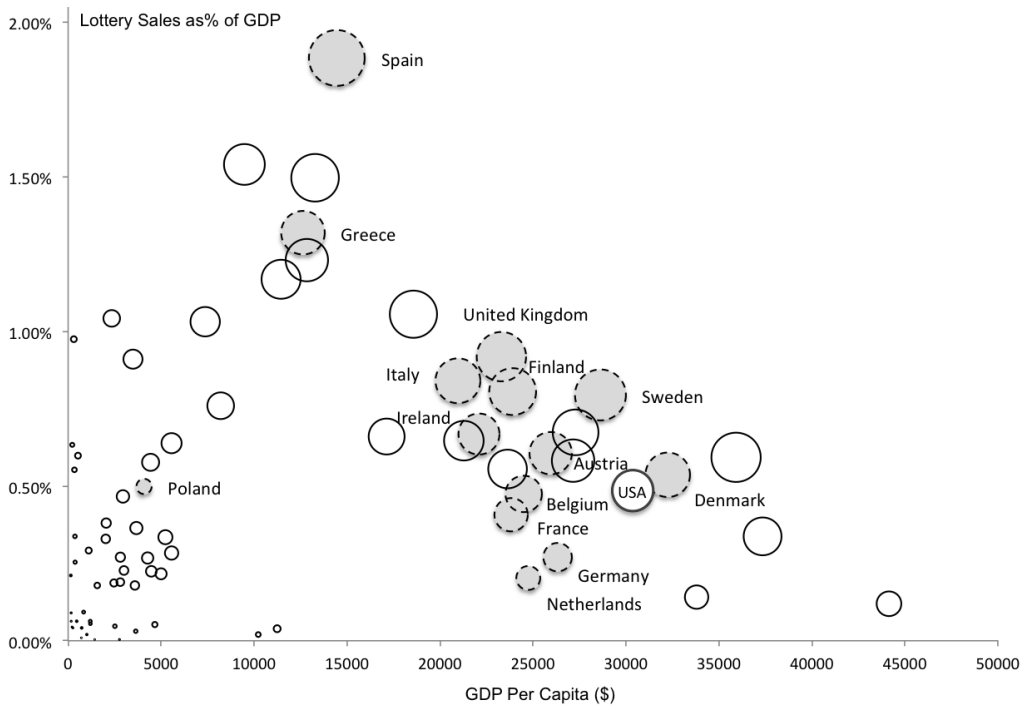
cross-section on individual stock level, cannot replicate the negative relation between returns and neither the idiosyncratic skewness documented by Boyer *et al.* (2010), nor the systematic skewness presented by Harvey & Siddique (2000).

Table 2.1 presents an overview of the previous empirical results investigating both idiosyncratic volatility and idiosyncratic skewness.

2.6 Gambling in Europe

Graph 2.1 plots each country's percentage of lottery sales on GDP against GDP per capita and shows an inverted U relationship between the two variables implied also by Kaizeler & Faustino (2008). Lottery sales increase with increasing GDP per capita until the point when the relation reverses and lottery becomes an inferior good.

Figure 2.1: Lottery Sales as a Percentage of GDP



Source: Author's computations based on lottery sales data from Garrett (2001) and GDP per capita data from World Bank (2008) .

Notes: Both lottery sales and GDP per capita are for 1997. Size of the bubbles reflects lottery sales per capita. Countries investigated in this study are marked with grey color.

EU countries investigated in this study appear to show decreasing lottery sales with GDP, with the exception of Poland, which has significantly lower GDP and lottery sales.

Several European countries show similar lottery sales to the U.S. market and therefore pose relevant alternatives to test lottery preferences in stock markets. Additionally, the differences between European countries allow to test whether countries with a higher propensity for state lotteries also face a higher lottery premium on stock markets. Using data from Europe also allows to avoid the danger that the previous findings are dependent only on a sample of U.S. data.

To proxy for a country's propensity to gamble, I use gross gaming revenue, which is calculated as the total sum of all players' contributions minus the winnings. In other words, gross gaming revenue represents the total net spending on lotteries and gambling. The main reason to use gross gaming revenue rather than total sales is that total sales are not always reported. For example for casinos there is no systematic way to measure turnover. Although total sales may better proxy for people's demand, I expect that the ratio between gross gaming revenue and turnover is similar in different countries and gross gaming revenue is therefore a valid proxy. All countries, where the data about total lottery sales are available, show gross gaming revenue to turnover ratio ranging from 40% to 50%.

Chapter 3

Hypotheses

The empirical evidence from the U.S. stock markets indicates that individual investors show propensity for lottery-type stocks, which are, as a result, overpriced and underperform the market portfolio. Ang *et al.* (2009) show that in both U.S. and European stock markets idiosyncratic volatility is a priced factor in cross-sectional regressions and stocks with higher idiosyncratic volatility exhibit lower future returns. Bali *et al.* (2011), however, show that idiosyncratic volatility might be priced because it proxies for extreme positive past returns. Stocks with extreme positive returns may appear to be like lotteries and the *"iv puzzle"* can be explained by lottery preferences of investors.

If these findings are robust to different data samples and different markets, the effects of lottery characteristics should also be observable in European stock markets.

First, I expect the portfolio of lottery stocks to underperform the rest of the market. If there is a sufficient number of investors who find lottery-type stocks more attractive, and are willing to pay higher prices for these stocks, then their future average risk-adjusted returns should be lower compared to the market. To test this hypothesis I follow empirical definition of lottery-type stock presented by Kumar (2009).

H1: Lottery premium hypothesis: Stocks featuring lottery characteristics; i.e. low price, high idiosyncratic skewness and high idiosyncratic volatility, exhibit negative abnormal returns.

Second, I check whether the *"iv puzzle"* is significant on all investigated markets. Ang *et al.* (2009) observe the so-called *"iv puzzle"* individually in

France, Germany, Italy and the United Kingdom. I extend the sample for other EU countries and test whether the puzzling evidence can be found universally. The motivation for this hypothesis is simply that in order to attempt to explain the *"iv puzzle"* with lottery preferences, I first need to verify that the anomalous phenomenon occurs in the data sample.

H2: Idiosyncratic volatility puzzle hypothesis: Stocks with past high idiosyncratic volatility show lower future returns.

Third, I investigate whether extreme past returns can explain the *"iv puzzle"*. In particular, I replicate the test of Bali *et al.* (2011) on EU markets and check whether the pattern observed in the U.S. cross-sectional regression exists in other markets.

H3: Extreme returns and "iv puzzle" hypothesis: The negative relation between past idiosyncratic volatility and future returns reverses or remains insignificant after controlling for past extreme positive daily returns.

This hypothesis examines whether the underlying economic source of idiosyncratic volatility pricing could be investors' preference for lottery-type payoffs. I expect the past extreme returns to have a stronger predictive power than idiosyncratic volatility. This would indicate that it is not the idiosyncratic volatility itself that investors seek, but rather stocks with extreme positive returns.

Finally, motivated by the findings of Barsky *et al.* (1997) and Kallick *et al.* (1979) I expect regions with a higher propensity to gamble to show a higher preference for lottery-type stocks. Kumar (2009); Kumar *et al.* (2011b) show that investors located in regions with more favorable lottery environments proxied by religion and religiosity hold higher proportion of lottery-type stocks. If investors in countries with a higher gambling spending also exhibit a higher propensity for lottery-type stocks, these countries can be expected to show also more pronounced lottery premium.

H4: Propensity to gamble hypothesis: Countries with a higher propensity to gamble exhibit a higher lottery premium in stock markets.

Chapter 4

Measuring Lottery Characteristics

4.1 Data

To test the hypotheses presented in the previous chapter, I use an extensive data set comprising of daily returns on firms from 14 developed EU markets. The markets were selected based on the number of listed securities so that the portfolio level analysis can be performed efficiently. In particular, only markets and periods where data from more than 100 securities are available are included in the analysis.

I use local-currency-denominated returns and compute excess returns using local one-month or three-month T-bill rates or interbank offer rates, depending on their availability. Where daily T-bill or interbank rates are not available, monthly mean rates are used. The sample period begins in January 1980 and ends in January 2012, however the majority of countries have sufficient number of stocks available only in mid-1980's or beginning 1990's. The shorter data set for Poland starting in 1998 results in 151 monthly observations, which is a sufficient number for a time-series analysis.

There are large differences in the number of stocks available for each market. For the United Kingdom 6455 stocks are analyzed, for Spain only 254 stocks, and many countries have only about 100 stocks available for multiple periods. Therefore, the estimated factors may be more prone to estimation errors for countries with fewer stocks. On the other hand, a smaller number of countries would decrease our ability to compare the lottery premiums across countries.

All data are obtained from Datastream database. Table 4.1 shows the description of the data across countries.

Table 4.1: Description of Country Data Sets

Country	*Stock Exchange*	*Risk-Free Proxy*	*CU*	*Start*	*Months*	*Stocks*	*Observations*
Austria	Vienna SE	3 month interbank	EUR	1991	235	258	30534
Belgium	Euronext Brussels	3 month T-bill	EUR	1986	294	539	68065
Denmark	Copenhagen SE	3 month interbank	EUR	1988	271	441	61521
Finland	OMX Helsinki	1 month interbank	EUR	1990	247	318	37937
France	Euronext Paris	3 month interbank	EUR	1980	367	2251	278982
Germany	Frankfurt SE	1 month interbank	EUR	1980	367	1670	224632
Greece	Athens SE	3 month interbank	EUR	1990	247	486	70038
Ireland	Irish SE, London SE	3 month interbank	EUR	1986	295	208	29320
Italy	Milan SE	3 month T-bill	EUR	1983	330	762	108369
Netherlands	Euronext Amsterdam	1 month interbank	EUR	1980	367	435	94189
Poland	Warsaw SE/Continuous	1 month interbank	PLN	1998	151	598	39808
Spain	Madrid SE	3 month interbank	EUR	1989	259	254	36237
Sweden	OMX Stockholm	3 month T-bill	SEK	1986	294	1459	115565
United Kingdom	London SE	1 month T-bill	GBP	1980	367	6455	656495

Notes: For each country the data set starts in the year stated in the "Start" column and ends in January 2012. All data for a particular country are denominated in its local currency reported in the "CU" column. Column "Months" reports the number of monthly observations, "Stocks" report the overall number of stocks analyzed for each country, "Observations" report the total number of stock-month observations used in Fama & MacBeth (1973) regressions.

In total, the overall data set comprises of more than 37 million observations for 8,392 trading days and 16,134 stocks listed on 14 European stock markets.

All equities within each market, which are traded on its main stock exchange, are included in the dataset. Polish stocks from both the Warsaw Stock Exchange and the Warsaw Continuous are included. Only the Irish data set also consists of stocks listed abroad on the London Stock Exchange because around one third of the Irish primary-quoted securities are listed there. This enables us to create an Irish lottery-type portfolio as the number of stocks listed only on the Irish Stock Exchange would not be sufficient. Non-primary-quoted securities are excluded to avoid cross-listings. To remove non-common equities I follow Ince & Porter (2006) and perform similar screens of the data to exclude closed-end funds, REIT's and preferred stocks.

The Datastream practice of rounding return index, documented by Ince & Porter (2006), can cause non-trivial differences in measuring idiosyncratic volatility using daily data. To avoid this problem, I calculate returns from dividends and prices adjusted for splits and other capital changes rather than from return index. Since Datastream reports stock price as constant after it stops trading, I set all constant values at the end of the time span to missing.

Data acquired from Datastream with daily frequency are corrupted by recording errors, which have a significant impact on lottery characteristic estimates. For instance, the average of maximum daily return per month for Belgium measured before filtering the recording errors is 49.52% with a standard error of 6879%. The focus of this study is on stocks with lottery-type payoffs and extreme positive returns and therefore Winsorization may bias its inferences. For this reason the recording errors identified in the data set are eliminated following methodology presented by Ince & Porter (2006) adjusted for daily data frequency and extreme values.

Ince & Porter (2006) set as missing monthly returns R_m and R_{m-1} if R_m, or R_{m-1} is more than 300% and the cumulative return over the two periods $(1 + R_m)(1 + R_{m-1}) - 1$ is lower than 50%. This approach does not eliminate errors with extreme values, which I identified mainly for very cheap stocks. For example, the Belgian stock VPK Packaging Strip has, according to Datastream, a closing price on 10/28/2010 equal to 0.001€, on 10/29/2010 its price rocketed to 2.997€ resulting in a daily return of 299600% and dropped back to 0.02€ on 11/25/2010. This extreme reversed return would not be filtered out, because the cumulative return over the described period is more than 50%. Therefore I adjust the condition on the cumulative return and I assign missing values to

$R_t, R_{t+1}, ..., R_{t+20}$ or $R_t, R_{t-1}, ..., R_{t-20}$ if $R_t > 300\%$ and the cumulative return over the 20 day period is lower than 1/6 of the extreme return on day t, where R_t is a return on stock on day t.

Other extreme positive daily returns above 2000% are caused by dividend payments. For example for Italian stock Telecom Italia RNC Datastream reports for 6/16/1988 adjusted price 0.31€ and a dividend payment of 44.46€. The error appears to be in currency exchange. Although the dividend payment is, according to Datastream, denominated in euros, it rather corresponds to the value denominated in old Italian lira, as the stock prices denominated in ITL are 559.48 ITL on 6/15/1988 and 503.91 ITL on 6/16/1988. Therefore both the price level and price drop on the ex-dividend date match the size of the dividend if denominated in ITL.

Since it is not reliably possible to identify errors in dividend payments using data from Datastream, these extreme values are not corrected. However, because Italy's data set is the most affected by errors, which led to spurious results, I rather use returns not adjusted for dividend payments for this country.

4.1.1 Market Factor

The market factor for each country is computed as an excess return of all stocks in the local country portfolio over de-annualized risk-free proxy weighted by market value from previous day.

In markets, which are dominated by one or few stocks, value-weighted market return can be highly correlated with a small number of stocks and its ability to represent volatility of the overall market is lower. This can have an important impact on measuring idiosyncratic volatility, which would more represent volatility uncorrelated with the few dominating stocks rather than volatility uncorrelated with the overall market.

In this study, the Finnish stock market is highly dominated by Nokia, which in multiple periods represents more than 70% of the total market capitalization. To eliminate its dominant effect, I perform all tests using the Finnish portfolio excluding Nokia. Since I am mainly interested in the lottery preferences of home investors, which can be compared to the propensity to gamble on a country level, the elimination of Nokia, which was in 1998 by more than three quarters owned by foreign investors (Liljeblom & Loflund 2005), should not have a relevant impact on my inferences.

4.2 Idiosyncratic Volatility

There are various methodologies used to measure idiosyncratic volatility in previous literature. They differ mainly in the period over which idiosyncratic volatility is measured and in the model used to explain volatility in returns. To verify that my results are robust to the method used to measure idiosyncratic volatility, I use three different methodologies following three related papers.

4.2.1 Three-Factor Model

First, I follow Ang *et al.* (2009) who measure idiosyncratic volatility to test the idiosyncratic volatility puzzle. Similarly to Fama & French (1993) they use model with three local factors: a market excess return, a size factor, and a value factor.

To obtain the size and value factor I rank all stocks that report market capitalization and positive book-to-market ratio into 6 portfolios. Following Fama & French (1993) I exclude all financial and insurance companies because of their higher leverage. First, stocks under median market capitalization are classified as small-cap (S), the rest as large-cap (B). Second, stocks are divided to three groups based on their book-to-market ratio. The firms with the lowest 30% value are ranked as L, the highest 30% as H and the rest as M. Intersection of this grouping forms 6 value-weighted portfolios LS, MS, HS, LB, MB, and HB. Finally, daily size and value factors are defined as:

$$SMB = \frac{1}{3}(HS + MS + LS) - \frac{1}{3}(HB + MB + LB), \tag{4.1}$$

$$HML = \frac{1}{2}(HB + HS) - \frac{1}{2}(LB + LS). \tag{4.2}$$

Stocks are grouped into portfolios on the last trading day in June and *SMB* and *HML* factors are calculated using daily value-weighted returns from July to June in the next year.

Following Ang *et al.* (2009), I estimate idiosyncratic volatility of an individual stock with respect to the three-factor model:

$$r_{i,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + \epsilon_{i,d}, \tag{4.3}$$

where $r_{i,d}$ is a daily excess return of stock i and MKT_d, SMB_d, and HML_d are daily factors.

The idiosyncratic volatility $IVOL3_{i,t}$ of stock i in month t is defined as

the standard deviation of the residuals $\epsilon_{i,d}$ obtained by estimating equation 4.4 over month $t-1$:

$$IVOL3_{i,t} = \sqrt{\frac{1}{N(t)} \sum_{d \in S(t)} \epsilon_{i,d}^2}, \tag{4.4}$$

where $N(t)$ denotes a number of trading days and $S(t)$ is a set of days in month t.

4.2.2 Four-Factor Model

In his empirical definition of lottery-type stock Kumar (2009) uses the Carhart (1997) four-factor model to estimate idiosyncratic volatility. To construct the additional momentum factor I calculate cumulative monthly returns from month $t-13$ to $t-2$ for all stocks reporting market capitalization at the end of month $t-1$. Based on the cumulative return I rank the bottom 30% stocks as low return (LR) and the top 30% stocks as high return (HR). Small (S) and large-cap (B) stocks are again divided by the median market capitalization at the end of month $t-1$. The momentum factor UMD for all days in month t is defined as:

$$UMD = \frac{1}{2}(SHR + BHR) - \frac{1}{2}(SLR + BLR), \tag{4.5}$$

where SHR, BHR, SLR, and BLR are daily returns of portfolios formed as an intersection of the two ranking methods weighted by market value on a previous day.

Idiosyncratic volatility $IVOL4_{i,t}$ for month t and stock i is again measured as a standard deviation of residuals obtained by fitting the four factor model:

$$r_{i,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + u_i UMD_d + \epsilon_{i,d}, \tag{4.6}$$

Following Kumar (2009) I use a six-month period of previous daily returns to estimate idiosyncratic volatility.

Mean values of daily factors for all countries are presented in table 4.2. All average market factors are positive with the exception of the negative Greek market factor, which reflects the poor performance of the Greek portfolio over the sample period. The low market factor for Poland is caused partially by higher interbank rates and partially by the stock market slump in 2008. Many

SMB factors are negative indicating that on daily average small-capitalization stocks did not outperform large-capitalization stocks.

Table 4.2: Country Daily Factors

Country	*MKT*	*SMB*	*HML*	*UMD*
Austria	0.0036 (1.029)	0.0088 (1.063)	0.0383 (1.077)	0.0242 (1.158)
Belgium	0.0202 (1.038)	-0.0138 (0.851)	0.0221 (0.921)	0.1191 (1.626)
Denmark	0.0212 (0.986)	-0.0188 (0.939)	0.0309 (0.976)	0.0275 (0.967)
Finland	0.0233 (1.188)	-0.0116 (1.077)	0.0083 (1.109)	0.0464 (1.165)
France	0.0145 (1.083)	0.0000 (0.913)	0.0371 (0.756)	0.0200 (0.808)
Germany	0.0163 (1.074)	-0.0120 (0.808)	0.0424 (0.730)	0.0117 (0.923)
Greece	-0.0236 (1.614)	-0.0017 (1.170)	0.0346 (1.094)	0.0213 (1.376)
Ireland	0.0089 (1.347)	-0.0058 (1.574)	0.0526 (1.948)	-0.0514 (2.071)
Italy	0.0031 (1.300)	-0.0121 (1.017)	0.0182 (1.159)	0.0296 (0.956)
Netherlands	0.0332 (1.091)	-0.0108 (0.907)	0.0148 (0.910)	0.0377 (1.093)
Poland	0.0018 (1.462)	0.0261 (1.068)	0.0783 (1.087)	0.0258 (1.085)
Spain	0.0286 (1.218)	-0.0317 (0.907)	0.0312 (0.911)	0.0465 (0.947)
Sweden	0.0358 (1.319)	-0.0233 (0.992)	0.0236 (1.056)	-0.0072 (1.139)
United Kingdom	0.0654 (1.017)	0.0477 (0.840)	0.0192 (0.564)	0.0625 (0.733)

Notes: The table reports means of local daily factors for each country. Standard deviations are reported in parentheses. MKT is a value-weighted return on the market portfolio, SMB and HML are size and value factors of Fama-French model, UMD is momentum factor of Carhart's four-factor model. All factors are denominated in local currencies.

4.2.3 One-Factor Model

The last measure of idiosyncratic volatility is motivated by the study of Bali *et al.* (2011), who use a simple one-factor model:

$$r_{i,d} = \alpha_i + \beta_i MKT_d + \epsilon_{i,d}. \tag{4.7}$$

The model is fitted using daily data over previous one month.

4.3 Idiosyncratic Skewness

To measure idiosyncratic skewness I adopt the methodology of Harvey & Siddique (2000). I estimate the following two factor model of the excess market return and squared excess market return:

$$r_{i,d} = \alpha_i + \beta_i MKT_d + \gamma_i MKT_d^2 + \epsilon_{i,d}. \tag{4.8}$$

The idiosyncratic skewness $ISKEW_{i,t}$ of stock i in month t is then defined as a skewness of residuals $\epsilon_{i,d}$ from equation 4.8 estimated over previous six months:

$$ISKEW_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \epsilon_{i,d}^3}{IVOL_{i,t}^3}, \tag{4.9}$$

where $IVOL_{i,t}$ is idiosyncratic volatility estimated by fitting the two factor model from equation 4.8.

4.4 Maximum Return

Maximum return is defined in line with Bali *et al.* (2011) as a maximum daily return within a month:

$$MAX_{i,t} = max(R_{i,d}), \tag{4.10}$$

where $R_{i,d}$ is a daily return of stock i.

Stocks that were not traded on all days and did not exhibit any positive price change during the month have zero maximum daily return. In some periods and some markets the number of stocks with zero maximum return is more than 20%.

Table 4.3 shows correlations between each lottery characteristic for the United Kingdom. Correlations for other countries show similar patterns and are not reported.

Table 4.3: Correlations of Lottery Characteristics

	IVOL3	*IVOL4*	*IVOL1*	*ISKEW*	*MAX*
IVOL3	1.000				
IVOL4	0.429	1.000			
IVOL1	0.990	0.429	1.000		
ISKEW	0.052	0.101	0.051	1.000	
MAX	0.961	0.407	0.977	0.090	1.000

Notes: The table reports correlations of monthly lottery characteristics for the United Kingdom. IVOL3 is idiosyncratic volatility estimated from Fama-French three-factor model using daily returns over previous month. IVOL4 is idiosyncratic volatility estimated by fitting four-factor model over previous six months of daily data. IVOL1 is idiosyncratic volatility estimated over the past month of daily returns in the one-factor model. ISKEW denotes idiosyncratic skewness measured by fitting a two-factor model of the excess market return and squared excess market return over past six months and MAX is maximum daily return over the past month. The methodology used to measure these variables is described in sections 4.2 - 4.4.

All lottery characteristics are positively correlated. IVOL3, IVOL1 and MAX have the highest correlation coefficient exceeding 0.95. All three variables are estimated over the same period of past one-month daily returns. The estimates of idiosyncratic volatility by fitting the three-factor model (IVOL3) or one-factor model (IVOL1) are very similar with a correlation coefficient of 0.977. Correlation of IVOL4 with IVOL3, IVOL1 and MAX is lower (around 0.4) because of longer estimation period of six months. The lowest correlation with remaining characteristics shows idiosyncratic skewness.

Table 4.4 shows descriptive statistics of each country's lottery characteristics. For all countries IVOL4 is higher than IVOL1 and IVOL1 is higher than IVOL3. Higher IVOL4 is a consequence of a longer estimation period of six months compared to only one month in case of IVOL3 and IVOL1. Beta coefficients estimated for a one month period fit the data better and cause lower measures of idiosyncratic volatility. Because the three-factor model used to estimate IVOL3 can better explain the volatility in returns than simple CAPM used for IVOL1, estimates of IVOL3 are lower.

Table 4.4: Descriptive Statistics of Lottery Characteristics

Country	*IVOL3*	*IVOL4*	*IVOL1*	*ISKEW*	*MAX*
Austria	1.50	1.88	1.63	0.38	4.04
	(2.67)	(2.89)	(2.88)	(2.73)	(10.17)
Belgium	3.32	4.12	3.52	0.54	11.38
	(29.59)	(22.61)	(33.90)	(2.63)	(155.39)
Denmark	1.77	2.19	1.89	0.39	5.03
	(2.72)	(2.62)	(3.04)	(3.04)	(13.24)
Finland	1.97	2.30	2.15	0.42	5.67
	(2.22)	(2.11)	(2.39)	(1.80)	(8.37)
France	2.16	2.70	2.31	0.52	6.21
	(4.32)	(4.07)	(4.74)	(2.64)	(20.89)
Germany	2.91	3.42	3.10	0.69	8.79
	(16.11)	(10.63)	(16.33)	(2.20)	(76.39)
Greece	2.26	2.57	2.48	0.41	6.49
	(2.24)	(1.76)	(2.46)	(1.52)	(10.63)
Ireland	1.84	2.25	2.01	0.39	5.33
	(2.80	(2.58)	(3.14)	(2.37)	(11.05)
Sweden	3.00	3.46	3.08	0.57	8.36
	(6.42)	(4.05)	(6.34)	(1.95)	(28.76)
Italy	1.66	1.92	1.82	0.46	4.82
	(1.49)	(1.37)	(1.67)	(1.41)	(6.17)
Netherlands	1.40	1.65	1.51	0.42	4.00
	(2.29)	(2.26)	(2.43)	(1.78)	(8.10)
Poland	2.65	3.06	2.88	0.63	7.45
	(2.39)	(2.24)	(2.61)	(1.33)	(9.01)
Spain	1.56	1.84	1.69	0.64	4.63
	(1.56)	(1.49)	(1.69)	(1.70)	(7.00)
United Kingdom	1.88	2.37	2.01	0.75	5.48
	(5.22)	(5.17)	(5.67)	(2.80)	(29.09)

Notes: The table lists average estimated lottery characteristics over the sample period for all countries. IVOL3 is idiosyncratic volatility estimated from Fama-French three-factor model using daily returns over previous month. IVOL4 is idiosyncratic volatility estimated by fitting four-factor model over previous 6 months of daily data. IVOL1 is idiosyncratic volatility estimated over past month of daily returns in one factor model. ISKEW denotes idiosyncratic skewness measured by fitting the two-factor model of the excess market return and squared excess market return over past 6 months and MAX is maximum daily return over the past month. The methodology used to measure these variables is described in sections 4.2 - 4.4.

Chapter 5

Portfolio-Level Analysis

In the first set of tests, I investigate whether portfolios sorted based on the lottery characteristics show the same return patterns as presented in recent empirical studies of the U.S. stock market. For brevity, some results are reported only for the United Kingdom, which has the highest number of stocks and the largest market capitalization.

5.1 Univariate Analysis

Table 5.1 presents average value-weighted monthly returns of decile portfolios formed by sorting all stocks listed at the London Stock Exchange on their idiosyncratic volatility from past month. The first decile portfolio "Low IVOL3" includes stocks with the lowest idiosyncratic volatility; "High IVOL3" is portfolio of stocks with the highest idiosyncratic volatility. The difference between the first and last decile is negative, although only -0.0279%, showing that high-idiosyncratic-volatility portfolio earns slightly lower value-weighted return. The difference in performance is stronger after adjusting for risk, the alpha differential between high and low idiosyncratic volatility portfolios is -0.561%. Therefore, consistent with the assumption that investors prefer stocks with high idiosyncratic volatility, high idiosyncratic stocks earn 6.732% lower average annual returns.

Looking more closely at the return pattern, it is evident that returns do not evenly decline as idiosyncratic volatility increases. Going from decile one to five, both value-weighted return and alpha increase. On the contrary, over deciles six to ten both measures decrease. This decline is more significant for alphas because higher idiosyncratic-volatility deciles are also characterized

Table 5.1: Returns on Portfolios of Stocks Sorted by IVOL3

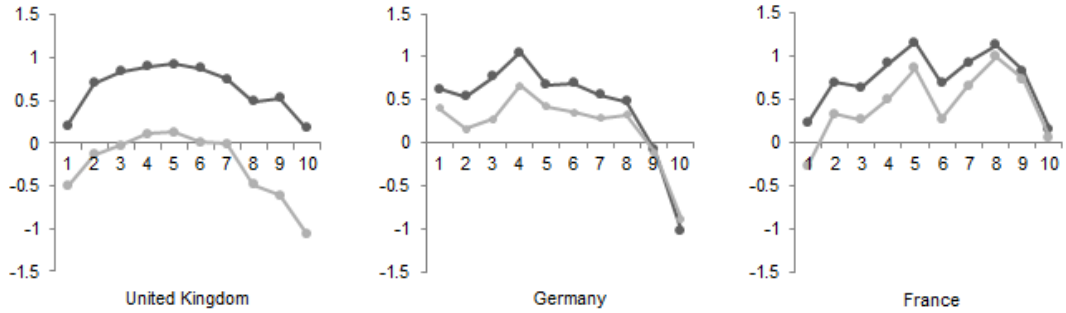
Decile	*Weighted Return*	*4-factor Alpha*	*Average ISKEW*	*Average MAX*	*Average IVOL3*	*Average Beta*
Low IVOL3	0.208	0.501	0.458	0.248	0.104	0.187
2	0.696	-0.139	0.659	1.120	0.456	0.340
3	0.837	-0.025	0.736	1.980	0.780	0.487
4	0.898	0.108	0.690	2.613	1.008	0.580
5	0.923	0.132	0.670	3.268	1.241	0.629
6	0.874	0.011	0.686	4.005	1.502	0.631
7	0.754	-0.007	0.708	4.922	1.828	0.737
8	0.491	-0.489	0.747	6.305	2.294	0.802
9	0.529	-0.619	0.839	8.747	3.093	0.884
High IVOL3	0.180	-1.061	1.133	20.489	.6.338	0.973

Notes: The table reports value-weighted returns and four-factor model alphas of decile portfolios formed by sorting all stocks listed on London Stock Exchange based on their idiosyncratic volatility. Average idiosyncratic volatility, idiosyncratic skewness, average maximum daily return and Beta from the three-factor model are reported for each portfolio.

by higher betas. In addition, two other lottery characteristics, idiosyncratic skewness and maximum daily return, are also on average higher for portfolios with higher idiosyncratic volatility.

Figure 5.1 shows that a similar pattern is also evident on the German market, where the return differentials are even higher (19.66% raw return differential, 15.44% alpha differential). Stocks listed on the Paris Stock Exchange show worse performance for high idiosyncratic stocks only when measured by raw returns and the difference is only 0.726% on an annual basis. Nonetheless, the decline of alphas and value-weighted returns over the three highest idiosyncratic volatility deciles remains.

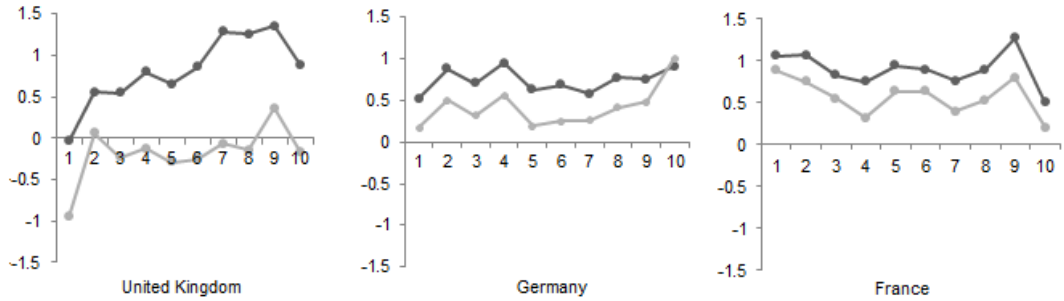
Figure 5.1: Returns on Portfolios of Stocks Sorted by IVOL3



Notes: Figures display value-weighted returns (dark line) and alphas (light-line) of decile portfolios formed by sorting stocks on idiosyncratic volatility. Portfolio one is the portfolio of stocks with the lowest idiosyncratic volatility, number ten is portfolio of stocks with the highest idiosyncratic volatility estimated by three-factor model. Alpha is a constant term from four-factor model.

Figure 5.2 and table 5.2 show decile portfolios formed by sorting stocks based on their idiosyncratic skewness. Both raw and risk-adjusted return differentials between the high-idiosyncratic skewness portfolio and the low-idiosyncratic skewness portfolio are positive and significant. Value-weighted and risk-adjusted annual return differentials are 11.076% and 12.792%.

Figure 5.2: Returns on Portfolios of Stocks Sorted by ISKEW



Notes: Figures display value-weighted returns (dark line) and alphas (light-line) of decile portfolios formed by sorting stocks on idiosyncratic skewness. Portfolio one is the portfolio of stocks with the lowest idiosyncratic skewness, number ten is portfolio of stocks with the highest idiosyncratic skewness estimated by three-factor model. Alpha is a constant term from the four-factor model.

The only evidence of positively priced idiosyncratic skewness is presented in the last decile portfolio which exhibits -5.676% raw and -6.276% risk-adjusted lower annual return. This effect is consistent with the assumption that investors prefer skewed stocks but only for extreme values of skewness.

Table 5.2: Returns on Portfolios of Stocks Sorted by ISKEW

Decile	*Weighted Return*	*4-factor Alpha*	*Average IVOL3*	*Average MAX*	*Average ISKEW*	*Average Beta*
Low ISKEW	-0.040	-0.955	1.694	2.646	-4.393	0.403
2	0.553	0.056	1.673	3.681	-1.321	0.586
3	0.548	-0.232	1.639	4.053	-0.366	0.707
4	0.794	-0.127	1.662	4.405	0.138	0.756
5	0.652	-0.290	1.720	4.793	0.518	0.781
6	0.857	-0.248	1.819	5.294	0.897	0.761
7	1.280	-0.063	1.899	5.764	1.342	0.727
8	1.251	-0.141	1.981	6.246	1.933	0.661
9	1.356	0.360	2.036	6.789	2.881	0.562
High ISKEW	0.883	-0.163	2.564	10.045	5.688	0.374

Notes: The table reports value-weighted returns and four-factor model alphas of decile portfolios formed by sorting all stocks listed on the London Stock Exchange based on their idiosyncratic skewness. Average idiosyncratic volatility, idiosyncratic skewness, average maximum daily return and Beta from the three-factor model are reported for each portfolio.

Different return patterns of idiosyncratic skewness on other markets are evident from figure 5.2. Although portfolios on the French market show an even larger return drop when moving from decile nine to ten, the German portfolios show the exact opposite effect. Overall, idiosyncratic skewness appears to have weaker pricing effects compared to idiosyncratic volatility.

The third group of decile portfolios reported in table 5.3 is sorted based on MAX, the maximum daily return from the previous month.

The most significant difference in returns is between the lowest MAX portfolio and portfolio two. The first portfolio is by a large part formed by stocks that did not exhibit any positive price change over the past month, often less-

Table 5.3: Returns on Portfolios of Stocks Sorted by MAX

Decile	*Average return*	*4-factor Alpha*	*Average ISKEW*	*Average IVOL3*	*Average MAX*	*Average Beta*
Low MAX	-4.166	-5.366	1.177	0.492	0.158	0.297
2	0.501	0.328	0.243	0.732	0.317	0.266
3	0.556	0.828	0.286	0.837	0.897	0.401
4	0.721	0.946	0.511	1.013	1.977	0.564
5	0.866	1.045	0.578	1.241	2.866	0.638
6	0.929	1.077	0.630	1.475	3.824	0.701
7	0.839	1.088	0.735	1.760	4.918	0.752
8	0.894	1.066	0.866	2.172	6.476	0.803
9	1.108	1.204	1.099	2.878	9.254	0.862
High MAX	0.630	0.683	2.004	5.843	23.000	0.898

Notes: The table reports value-weighted returns and four-factor model alphas of decile portfolios formed by sorting all stocks listed on the London Stock Exchange based on their maximum daily return from previous month. Average idiosyncratic volatility, idiosyncratic skewness, average maximum daily return and Beta from the three-factor model are reported for each portfolio.

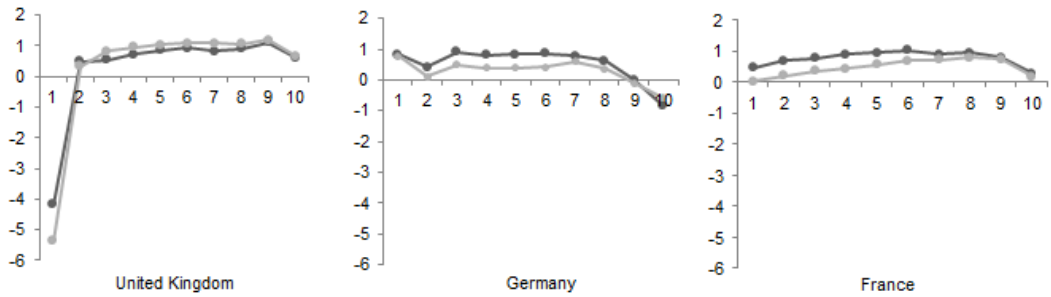
frequently traded stocks. On the London Stock Exchange these past losers exhibit on average negative returns also in the next month and cause the large difference in returns compared to the second decile portfolio. Because the number of stocks with zero MAX is in several periods higher than 10%, sometimes even more than 20% of the whole market, all these stocks fall into the first decile portfolio. As a consequence, the second and third portfolios do not contain zero-MAX stocks and show relatively higher returns.

To correct for this effect, which is the most apparent for the United Kingdom, I repeat the portfolio sorting based on MAX without zero. The adjusted MAX variable is defined as maximum from all non-zero daily returns if at

least one daily return is non-zero and zero if all returns are zero. Returns on portfolios formed by the adjusted MAX measure are plotted in figure 5.4. In comparison with the original MAX deciles, the effect of lower returns for past losers is more gradual and distributed over the first three portfolios.

For all three countries, the returns of MAX decile portfolios decrease over the top two portfolios as shown in figure 5.3. Also the difference between average MAX is highest between the last two portfolios. Portfolio nine and ten have an average MAX of 9.3% and 23.0% and the difference in their performance is 5.736% for raw value-weighted returns and 6.252% for risk-adjusted returns on an annual basis. This is consistent with the assumption that investors have a preference for stocks with potential extreme return and they may accept higher prices and lower returns for stocks with extreme past returns.

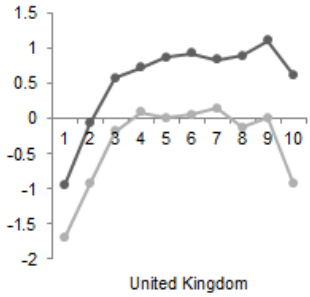
Figure 5.3: Returns on Portfolios of Stocks Sorted by MAX



Notes: Figures display value-weighted returns (dark line) and alphas (light-line) of decile portfolios formed by sorting stocks on maximum daily return over the previous month. Portfolio one is the portfolio of stocks with the lowest maximum daily return, number ten is a portfolio of stocks with the highest maximum daily return. Alpha is a constant term from the four-factor model.

All three examples show some evidence of lower returns for extreme values of lottery characteristics. Not surprisingly all three groups of decile portfolios show an increase in average values in the other two lottery characteristics. Idiosyncratic volatility and MAX increase monotonically from the first decile ISKEW portfolio to the last decile ISKEW portfolio. Similarly MAX and ISKEW grow over portfolios sorted by MAX. Therefore it is hard to determine which lottery characteristic should the observed return patterns be attributed to or whether their pricing effects are overlapping.

Figure 5.4: Returns on Portfolios of Stocks Sorted by MAX without Zero



Notes: Figures display value-weighted returns (dark line) and alphas (light-line) of decile portfolios formed by sorting stocks on maximum daily return on days with price change over previous month. Portfolio one is the portfolio of stocks with the lowest maximum daily return, number ten is a portfolio of stocks with the highest maximum daily return. Alpha is a constant term from the 4-factor model.

5.2 Lottery-Type Portfolio

To construct the lottery-type portfolio I follow Kumar (2009). I group all stocks on each market based on idiosyncratic volatility, idiosyncratic skewness and price. Price is price unadjusted for capital changes, idiosyncratic volatility is measured by the four-factor model and idiosyncratic skewness by the two-factor model estimated over the past six months. Stocks in the lower 50th price percentile, higher 50th idiosyncratic volatility percentile and higher 50th idiosyncratic skewness percentile form the lottery-type portfolio. Oppositely, stocks in the higher 50th price percentile, lower 50th idiosyncratic volatility percentile and lower 50th idiosyncratic skewness percentile form the nonlottery-type portfolio. The portfolio of the remaining stocks is identified as "Other portfolio".

Table 5.4 reports the descriptive statistics of lottery-type, nonlottery-type and other stocks. Lottery-type portfolio consists of only 1.37% of the total market capitalization. On the contrary, nonlottery-type stocks stand for 58.72%. This illustrates the fact that lottery-type stocks are usually stocks of small companies. Stocks in a lottery-type portfolio have also higher betas for SMB, HML and market factor. The lottery-type portfolio of the United Kingdom also shows higher average past return, however, this difference does not appear on all markets.

Next, the question of whether lottery-type portfolio gains lower returns by measuring raw, characteristic-adjusted and risk-adjusted returns on each

Table 5.4: Descriptive Statistics of Lottery-Type Stocks

Measure	*Lottery-Type*	*Nonlottery-Type*	*Others*
Number of stocks	332	326	1077
Percentage of the market	1.37%	58.72%	39.91%
Idiosyncratic volatility	4.13	1.18	2.14
Idiosyncratic skewness	2.67	-0.69	0.55
Stock price	39.48	614.69	400.22
Market beta	0.899	0.617	0.628
SMB beta	0.865	0.266	0.477
HML beta	0.195	0.072	0.096
UMD beta	-0.066	-0.002	-0.372
Firm size	26.61	1986.01	392.39
Book-to-market ratio	0.639	0.667	0.741
Past 12-month return	13.49	10.47	7.39

Notes: The table presents descriptive statistics of lottery-type portfolio, nonlottery-type portfolio and portfolio of other stocks for comparison. The number of stocks is the average number of stocks in each portfolio over all periods, the percentage of the market is the average share on market capitalization. For other characteristics averages over the sample period are reported.

country market is addressed.

First, table 5.5 reports means of the value-weighted returns over the sample period. LT stands for lottery-type portfolio, NL for nonlottery-type portfolio and OT for portfolio of other stocks. LT-NL and LT-OT are zero-cost portfolios with a long position in lottery-type portfolio and short position in nonlottery and other portfolio, respectively.

The lottery-type portfolio has a negative return for Germany, Spain and Sweden, but none of these returns is significantly different from zero. The same

Table 5.5: Value-weighted Returns of Lottery-Type Portfolio

Country	*LT*	*NL*	*OT*	*LT-NL*	*LT-OT*
Austria	0.517	0.511	0.394	0.006	0.123
	(0.482)	(0.354)	(0.338)	(0.423)	(0.367)
Belgium	0.939	0.622	0.722	0.317	0.217
	(0.476)	(0.258)	(0.358)	(0.404)	(0.379)
Denmark	0.078	0.567	0.798	-0.489	-0.720
	(0.451)	(0.342)	(0.321)	(0.393)	(0.344)
Finland	0.483	0.726	1.113	-0.243	-0.630
	(0.546)	(0.456)	(0.386)	(0.463)	(0.345)
France	0.896	0.922	0.831	-0.026	0.065
	(0.493)	(0.285)	(0.281)	(0.372)	(0.330)
Germany	-0.127	0.784	0.798	-0.910	-0.925
	(0.374)	(0.286)	(0.273)	(0.274)	(0.260)
Greece	0.411	0.511	0.423	-0.100	-0.012
	(0.850)	(0.548)	(0.570)	(0.648)	(0.508)
Ireland	1.143	0.430	0.548	0.748	0.507
	(0.903)	(0.290)	(0.405)	(0.867)	(0.825)
Italy	0.846	0.604	0.465	0.290	0.379
	(0.491)	(0.346)	(0.346)	(0.319)	(0.283)
Netherlands	0.533	0.487	1.129	0.149	-0.413
	(0.456)	(0.311)	(0.305)	(0.312)	(0.262)
Poland	0.479	0.944	0.562	-0.427	-0.049
	(0.814)	(0.649)	(0.547)	(0.690)	(0.541)
Spain	-0.001	1.048	1.211	-1.050	-1.212
	(0.52)	(0.370)	(0.363)	(0.378)	(0.352)
Sweden	-0.157	1.099	1.111	-1.290	-1.298
	(0.612)	(0.392)	(0.393)	(0.447)	(0.430)
United Kingdom	0.823	0.659	0.798	0.164	0.034
	(0.399)	(0.248)	(0.257)	(0.314)	(0.264)

Notes: The lottery-type portfolio (LT) is formed by stocks in the lower 50th price percentile, the higher 50th idiosyncratic volatility percentile and the higher 50th idiosyncratic skewness percentile. Nonlottery-type portfolio (NL) is the portfolio of stocks in the higher 50th price percentile, the lower 50th idiosyncratic volatility percentile and the lower 50th idiosyncratic skewness percentile. The remaining stocks form portfolio OT. LT-NL and LT-OT are zero-cost portfolios that place long position in lottery-type portfolio and short position in nonlottery-type portfolio and in portfolio of other stocks. Table reports mean of monthly value-weighted returns and standard errors in parentheses.

three countries exhibit negative and significant return on portfolio LT-NL with annual return difference of -10.92%, -15.48% and -15.576%. Negative returns on LT-OT are even higher (11.1%, 14.544%, 15.576%) and significant also for Denmark with lower return by -8.64% per annum. Although the difference in performance appears only on 4 markets, its magnitude is higher than the difference of -7.96% reported by Kumar (2009) for the U.S. market. Weighted returns of both LT-NL and LT-OT on other markets are not significantly different from zero.

Second, characteristic-adjusted returns are displayed in table 5.6. Returns adjusted for size, book-to-market and momentum effects are calculated using the Daniel *et al.* (1997) method. I form 125 benchmark portfolios as an intersection of 5 size quintiles, 5 book-to-market quintiles and 5 quintiles based on past 12-month returns. The characteristic adjusted returns are then calculated by subtracting the benchmark portfolio return from the individual return of each stock that forms the corresponding benchmark portfolio.

Results show that the lottery-type portfolio underperforms again in case of Germany, Spain and Sweden. Their characteristic-adjusted returns are significantly negative for all three LT, LT-NL and LT-OT portfolios. For Germany the lottery-type portfolio underperforms by -6.768% on an annual basis, the performance differentials are -7.248% compared to the nonlottery-type portfolio and -6.144% compared to other stocks. Performance measures listed in the same order are -4.62%, -4.164% and -5.124% for Spain and -10.044%, -11.34% and -11.076% for Sweden. Contrary to lottery-type portfolios, nonlottery-type portfolios do not outperform for any country as all characteristic-adjusted returns for NL portfolios are not significantly positive.

Finally, table 5.7 presents risk-adjusted returns measured as alpha coefficient from four-factor model estimated for five value-weighted portfolios. Performance differentials for LT-NL and LT-OT portfolios are again significant for Germany, Spain and Sweden, although Spain has negative return of LT-NL portfolio only at 10% significance level. Risk-adjusted differences in performance for LT-NL and LT-OT portfolios are also economically significant, accounting for more than 7% lower annual returns (Germany: -9.36%, 9.624%; Spain: -7.212%, -10.068%; Sweden: 11.604%, 12.42%). In addition, four more countries show evidence of lottery-type portfolio underperformance. The United Kingdom and Poland have significantly negative returns for both zero cost portfolios (United Kingdom: -7.344% / -6.504%; Poland: 18.624% / 10.956%; LT-NL / LT-OT on annual basis). The lottery-portfolio underper-

Table 5.6: Characteristic Adjusted Returns of Lottery-Type Portfolio

Country	*LT*	*NL*	*OT*	*LT-NL*	*LT-OT*
Austria	0.022	0.047	-0.026	-0.025	0.048
	(0.200)	(0.085)	(0.034)	(0.222)	(0.210)
Belgium	0.213	-0.204	0.058	0.416	0.154
	(0.204)	(0.139)	(0.055)	(0.214)	(0.233)
Denmark	-0.358	-0.082	0.045	-0.276	-0.403
	(0.245)	(0.107)	(0.052)	(0.287)	(0.262)
Finland	-0.335	-0.058	0.034	-0.277	-0.369
	(0.209)	(0.108)	(0.040)	(0.254)	(0.219)
France	-0.032	0.052	-0.034	-0.084	0.003
	(0.184)	(0.056)	(0.037)	(0.202)	(0.188)
Germany	-0.564	0.041	-0.052	-0.604	-0.512
	(0.239)	(0.049)	(0.042)	(0.252)	(0.230)
Greece	-0.225	0.032	-0.036	-0.257	-0.189
	(0.215)	(0.151)	(0.075)	(0.292)	(0.224)
Ireland	0.152	0.000	0.004	0.159	0.151
	(0.246)	(0.088)	(0.053)	(0.269)	(0.257)
Italy	0.130	0.011	-0.004	0.128	0.140
	(0.180)	(0.061)	(0.030)	(0.200)	(0.186)
Netherlands	-0.197	-0.140	0.011	0.018	-0.147
	(0.145)	(0.092)	(0.040)	(0.167)	(0.148)
Poland	0.045	0.041	-0.009	0.009	0.057
	(0.343)	(0.075)	(0.083)	(0.355)	(0.360)
Spain	-0.385	-0.038	0.042	-0.347	-0.427
	(0.150)	(0.071)	(0.054)	(0.170)	(0.163)
Sweden	-0.837	0.083	-0.038	-0.945	-0.823
	(0.214)	(0.053)	(0.058)	(0.225)	(0.220)
United Kingdom	0.063	-0.015	0.034	0.078	0.030
	(0.159)	(0.030)	(0.042)	(0.169)	(0.158)

Notes: The lottery-type portfolio (LT) is formed by stocks in the lower 50th price percentile, the higher 50th idiosyncratic volatility percentile and the higher 50th idiosyncratic skewness percentile. The nonlottery-type portfolio (NL) is a portfolio of stocks in the higher 50th price percentile, the lower 50th idiosyncratic volatility percentile and the lower 50th idiosyncratic skewness percentile. The remaining stocks form portfolio OT. LT-NL and LT-OT are zero-cost portfolios that place a long position in lottery-type portfolio and short position in nonlottery-type portfolio and in portfolio of other stocks. The table reports means of monthly characteristic-adjusted returns and standard errors in parentheses.

Table 5.7: Alpha of Lottery-Type Portfolio

Country	*LT*	*NL*	*OT*	*LT-NL*	*LT-OT*
Austria	0.265	0.471	0.265	-0.206	0.000
	[0.75]	[2.78]	[3.31]	[-0.49]	[-0.00]
Belgium	0.701	0.311	0.327	0.390	0.374
	[1.85]	[2.12]	[2.88]	[0.96]	[0.94]
Denmark	-0.092	0.250	0.479	-0.342	-0.571
	[-0.29]	[1.28]	[4.66]	[-0.87]	[-1.65]
Finland	-0.030	0.130	0.447	-0.160	-0.477
	[-0.10]	[0.52]	[3.79]	[-0.37]	[-1.48]
France	0.618	0.535	0.525	0.831	0.093
	[2.14]	[6.33]	[8.61]	[0.26]	[0.32]
Germany	-0.362	0.418	0.439	-0.780	-0.802
	[-1.61]	[4.50]	[5.68]	[-3.07]	[-3.50]
Greece	0.373	0.817	0.608	-0.444	-0.235
	[1.00]	[3.63]	[4.75]	[-0.95]	[-0.60]
Ireland	0.651	0.372	0.516	0.279	0.135
	[0.98]	[1.63]	[2.14]	[0.38]	[0.18]
Italy	0.926	0.623	0.520	0.303	0.407
	[3.50]	[6.42]	[8.09]	[1.01]	[1.49]
Netherlands	0.046	-0.236	0.555	0.189	-0.601
	[-0.17]	[-1.25]	[6.06]	[0.57]	[-2.08]
Poland	-0.546	1.006	0.367	-1.552	-0.913
	[-1.19]	[4.55]	[2.07]	[-2.69]	[-2.07]
Spain	-0.306	0.295	0.533	-0.601	-0.839
	[-1.04]	[2.12]	[6.24]	[-1.80]	[-2.61]
Sweden	-0.466	0.501	0.569	-0.967	-1.035
	[-1.49]	[5.13]	[4.41]	[-2.90]	[-3.07]
United Kingdom	-0.705	-0.093	-0.163	-0.612	-0.542
	[-2.87]	[-1.16]	[-1.77]	[-2.39]	[-2.23]

Notes: The lottery-type portfolio (LT) is formed by stocks in the lower 50th price percentile, the higher 50th idiosyncratic volatility percentile and the higher 50th idiosyncratic skewness percentile. The nonlottery-type portfolio (NL) is portfolio of stocks in the higher 50th price percentile, the lower 50th idiosyncratic volatility percentile and the lower 50th idiosyncratic skewness percentile. The remaining stocks form portfolio OT. LT-NL and LT-OT are zero-cost portfolios that place a long position in lottery-type portfolio and short position in nonlottery-type portfolio and in portfolio of other stocks. The table reports alpha intercept from the four-factor model and t-statistics in square brackets.

forms compared to other stocks by 7.212% per annum in the Netherlands and in Denmark by 6.852% at a 10% significance level.

Overall, the results show that lottery-type portfolio of Germany, Spain and Sweden underperforms irrespective of the benchmark and performance measure used at least by 6.144%, 4.164% and 10.044% on annual basis. The risk-adjusted performance measures indicate underperformance of lottery-type stocks in Denmark, the Netherlands, Poland and the United Kingdom. The remaining half of the countries; Austria, Belgium, Finland, France, Greece, Ireland and Italy, does not exhibit underperformance of lottery-type stocks measured on an aggregate portfolio level.

Chapter 6

Fama-MacBeth Regressions

To further investigate the pricing effects of lottery characteristics, I perform cross-sectional regressions following the approach of Fama & MacBeth (1973). The results contribute to the previous research of Ang *et al.* (2009) and Bali *et al.* (2011).

6.1 Idiosyncratic Volatility Puzzle

First, I replicate the test of Ang *et al.* (2009) and explore the puzzling pricing effect of idiosyncratic volatility on 14 EU markets. I use the same measure of idiosyncratic volatility IVOL3 estimated by fitting the three-factor model over the previous month to ensure comparability of the results. The original sample period of Ang *et al.* (2009) from 1980 to 2003 is prolonged to February 2012. This enables us to compare the results in a longer time frame and assess their validity in different time period. Most importantly, I extend the sample of individual countries from four countries (France, Germany, Italy and United Kingdom) to 14 countries and this way further verify whether the previous results are subject to data snooping as argued by Lo & A.C. (1990).

The table 6.1 reports the results of Fama & MacBeth (1973) regressions in 14 European markets and the associated Newey & West (1987) adjusted t-statistics. The statistically significant negative relation between idiosyncratic volatility and future excess returns exists only in half of the markets (Germany, Italy, Netherlands, Poland, Spain, Sweden, United Kingdom) and in Finland only at a 10% significance level.

Table 6.1: Idiosyncratic Volatility and Future Returns

Country	*Constant*	*IVOL3*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*BM*	*Lagged R*	*Avg. R^2*
Austria	-0.735	-.050	0.023	0.284	0.479	0.174	0.074	0.008	0.313
	[-1.79]	[0.50]	[0.07]	[0.89]	[1.77]	[2.60]	[1.98]	[1.39]	
Belgium	0.090	-0.991	0.418	0.209	-0.332	-0.017	0.325	0.004	0.284
	[0.30]	[-0.12]	[2.02]	[1.17]	[-1.59]	[-0.37]	[4.11]	[0.69]	
Denmark	-0.890	0.071	0.435	0.288	-0.076	0.033	0.882	0.014	0.247
	[-1.68]	[0.78]	[2.39]	[1.54]	[-0.32]	[0.55]	[5.38]	[3.36]	
Finland	1.423	-0.140	0.957	-0.122	0.050	-0.211	0.394	0.006	0.269
	[3.38]	[-1.76]	[3.07]	[-0.58]	[0.14]	[-3.28]	[3.31]	[1.47]	
France	1.211	-0.008	0.270	0.248	0.401	-0.159	0.083	-0.004	0.172
	[2.78]	[-0.11]	[1.36]	[1.70]	[2.53]	[-3.13]	[1.71]	[-0.88]	
Germany	1.016	-0.218	0.529	0.141	0.332	-0.112	0.188	0.003	0.156
	[2.92]	[-3.67]	[3.66]	[1.29]	[2.82]	[-3.00]	[1.74]	[0.84]	
Greece	1.521	0.021	-0.226	0.034	0.322	-0.272	0.338	0.007	0.205
	[1.45]	[0.17]	[-0.51]	[0.11]	[1.42]	[-2.58]	[2.32]	[1.08]	
Ireland	0.280	-0.141	0.676	0.441	0.180	0.014	0.330	0.011	0.368
	[0.42]	[-1.40]	[2.33]	[1.15]	[0.34]	[0.17]	[1.59]	[1.94]	

Country	*Constant*	*IVOL3*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*BM*	*Lagged R*	*Avg. R^2*
Italy	1.208	-0.536	0.701	-0.045	0.654	-0.147	-0.139	0.007	0.223
	[1.58]	[-2.89]	[2.15]	[-0.18]	[2.55]	[-2.65]	[-0.23]	[1.33]	
Netherlands	1.373	-0.472	0.671	-0.120	-0.123	-0.089	0.045	0.013	0.277
	[3.68]	[-5.32]	[3.25]	[-0.78]	[-0.62]	[-2.03]	[1.01]	[3.50]	
Poland	2.763	-0.251	1.226	0.287	-0.165	-0.428	0.311	0.022	0.219
	[2.20]	[-2.27]	[2.60]	[0.92]	[-0.45]	[-3.17]	[2.90]	[4.38]	
Spain	-0.120	-0.410	-0.002	0.599	0.362	0.158	0.543	0.012	0.275
	[-0.22]	[-4.41]	[-0.01]	[3.17]	[1.99]	[2.56]	[4.55]	[2.97]	
Sweden	1.391	-0.264	0.419	0.161	-0.053	-0.131	0.497	-0.001	0.190
	[2.14]	[-3.60]	[1.95]	[0.77]	[-0.26]	[-2.08]	[3.46]	[-0.20]	
United	0.932	-0.093	0.551	0.288	0.056	-0.161	0.239	0.014	0.104
Kingdom	[2.36]	[-2.25]	[3.82]	[2.00]	[0.70]	[-3.33]	[4.90]	[5.42]	

Notes: Table reports Fama & MacBeth (1973) regressions of monthly excess stock return on idiosyncratic volatility measured over past month with three-factor model, contemporaneous factor betas, β(MKT), β(SMB), β(HML), size (log market value) and book-to-market at the end of previous month and lagged return over previous 6 months. Reported t-statistics in square brackets are Newey & West (1987) adjusted t-statistics.

Although the statistical significance of IVOL3 factor for Germany, Italy and the United Kingdom is similar to the results of Ang *et al.* (2009), the economic significance is much lower. The coefficients for local currency denominated returns presented by Ang *et al.* (2009) are -1.769 (Germany), -1.865 (Italy) and -2.035 (United Kingdom), while my estimates are only -0.218 (Germany), -0.536 (Italy) and-0.093 (United Kingdom). The difference in results can be attributed to two differences in the data sample. First, I use a longer time span. The pricing effect of idiosyncratic volatility can depend on tested period and years 2004 to 2011 can potentially exhibit weaker pricing effects of idiosyncratic volatility. Second, my sample constitutes of all primary quoted stocks, while Ang *et al.* (2009) exclude very small stocks in each market. Ang *et al.* (2009) report that the idiosyncratic volatility effect is stronger among companies with larger market capitalization and therefore their results on the limited data sample can overestimate the IVOL3 effect.

For the markets, where IVOL3 is a significant factor, its predictive power is often stronger than β factor loadings or firm characteristics. The majority of countries show higher t-statistics for firm characteristics (size, book-to-market) than for $\beta(SMB)$ and $\beta(HML)$ factors. This can be caused by significant errors in estimating *beta* factors and by a low premium on small-cap and value companies during the sample period.

Remaining markets (Austria, Belgium, Denmark, France, Greece and Ireland) do not exhibit the so-called *"iv puzzle"*. This result is surprising especially for France, which shows both a statistically and economically significant negative relation between lagged IVOL3 and returns in the previous research of Ang *et al.* (2009). My results, although negative, show a very low t-statistic (-0.11). This difference in results could possibly be caused by the different time span investigated. Results of repeated tests on three different periods are reported in table 6.2.

The period from September 1980 until December 2003 covers exactly the same period as in Ang *et al.* (2009) and an even shorter period ending in December 1999 is reported for comparison. It is clear that the pricing effect of idiosyncratic volatility increases with shortening the sample period. Compared to the initial -0.11 t-statistic for the entire time period, time span used in previous research shows more significant results with t-statistic of -1.23. Although these results are still insignificant on 5% level, they demonstrate the effect of including years 2004-2012 in my sample. By shortening the period even more until December 1999 we get significant results with t-statistic equal to -2.28.

Table 6.2: France - Idiosyncratic Volatility and Future Returns

	Sep1980-Feb2012		*Sep1980-Dec2003*		*Sep1980-Dec1999*	
Constant	1.211	[2.78]	1.333	[2.55]	1.638	[2.77]
IVOL3	-0.008	[-0.11]	-0.102	[-1.23]	-0.184	[-2.28]
β(MKT)	0.270	[1.36]	0.304	[1.41]	0.706	[4.07]
β(SMB)	0.248	[1.70]	0.252	[1.68]	0.031	[0.28]
β(HML)	0.401	[2.53]	0.557	[3.28]	0.533	[3.00]
Size	-0.159	[-3.13]	-0.146	[-2.38]	-0.167	[-2.36]
BM	0.083	[1.71]	0.024	[0.89]	0.020	[0.76]
Lagged R	-0.004	[-0.88]	0.002	[0.38]	0.006	[1.08]
Avg. R^2	0.172		0.161		0.158	
No. of periods	378		281		233	

Notes: Table reports Fama & MacBeth (1973) regressions of monthly excess stock return on idiosyncratic volatility measured over past month with three-factor model, contemporaneous factor betas, β(MKT), β(SMB), β(HML), size (log market value) and book-to-market at the end of previous month and lagged return over previous 6 months. Reported t-statistic in square brackets are Newey & West (1987) adjusted t-statistics. Test covers individual stocks on French market for three different periods: full sample from September 1980 until February 2012, period used in Ang *et al.* (2009) from September 1980 until December 2003 and the shortest sample ending in December 1999.

The example of France demonstrates that the findings of Ang *et al.* (2009) are not robust to different estimation periods.

Another potential concern about the robustness of the negative coefficient on IVOL3 in Fama & MacBeth (1973) regression is that only stocks reporting book-to-market ratio are included in the test. In some countries even more than 30% of stocks are missing the book-to-market variable. These stocks often represent companies with smaller market capitalization and therefore their exclusion can bias results in favor of the *"iv puzzle"*.

Table 6.3: Idiosyncratic Volatility and Future Returns - Stocks with and without BM reported

Country	*Constant*	*IVOL3*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*Lagged R*	*Avg. R^2*	*No. of Stocks*
Finland	1.487	-0.039	1.036	-0.228	0.183	-0.231	0.003	0.245	302
	[4.15]	[-0.34]	[3.50]	[-1.10]	[0.61]	[-3.57]	[0.76]		
Reporting BM	1.624	-0.099	0.952	-0.128	0.071	-0.208	0.003	0.247	232
	[4.33]	[-1.06]	[3.01]	[-0.60]	[0.21]	[-3.29]	[0.72]		
Ireland	0.300	-0.175	0.553	0.648	0.214	0.051	0.001	0.298	205
	[1.22]	[-2.32]	[2.30]	[1.80]	[0.44]	[1.20]	[0.17]		
Reporting BM	0.880	-0.147	0.735	0.367	0.308	-0.053	0.009	0.337	114
	[1.61]	[-1.48]	[2.57]	[0.94]	[0.94]	[-0.72]	[1.54]		
Netherlands	0.450	-0.033	0.634	-0.172	-0.137	-0.008	0.012	0.241	429
	[3.68]	[-0.46]	[3.25]	[-1.04]	[-0.75]	[-0.27]	[3.41]		
Reporting BM	1.526	-0.417	0.594	-0.114	-0.066	-0.107	0.012	0.255	277
	[4.49]	[-4.37]	[2.83]	[-0.75]	[-0.32]	[-2.56]	[3.49]		

Country	*Constant*	*IVOL3*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*Lagged R*	*Avg. R^2*	*No. of Stocks*
United	0.898	0.026	0.537	0.287	0.013	-0.164	0.012	0.097	3984
Kingdom	[2.53]	[0.74]	[3.73]	[1.96]	[0.17]	[-3.41]	[4.90]		
Reporting BM	1.186	-0.093	0.561	0.280	0.060	-0.181	0.013	0.097	5936
	[3.05]	[-2.26]	[3.88]	[1.95]	[0.75]	[-3.70]	[5.09]		

Notes: Table reports Fama & MacBeth (1973) regressions of monthly excess stock return on idiosyncratic volatility measured over past month with three-factor model, contemporaneous factor betas, β(MKT), β(SMB), β(HML), size (log market value) and book-to-market at the end of previous month and lagged return over previous 6 months. Reported t-statistics in square brackets are Newey & West (1987) adjusted t-statistics. For each country first line reports results using all stocks and second line results when only stocks reporting book-to-market ratio are included in the regression.

Table 6.3 extends the Fama & MacBeth (1973) regressions also to stocks for which book-to-market variable is not reported. To verify the extent to which the results are influenced by omitting book-to-market variable in the regression specification, all regressions are repeated only on stocks reporting a book-to-market ratio. Only 5 countries, for which inclusion of stocks not reporting book-to market ratio changes significance of IVOL3 coefficient, are reported.

For Finland, the Netherlands and the United Kingdom, the coefficients on idiosyncratic volatility decrease in magnitude and significance after including stocks not reporting book-to-market ratio. This effect is mostly caused by omitting stocks not reporting book-to-market ratio rather than by omitting book-to-market variable in regression specification. In the case of the Netherlands and the United Kingdom, the results for stocks reporting book-to-market ratio in table 6.1 are similar to the results in table 6.3 after controlling for book-to-market. In the case of Finland, lower significance of IVOL3 when including all stocks is partially attributable to stocks not reporting book-to-market ratio and partially to omitting the book-to-market variable.

Ireland is the only country for which the coefficient on IVOL3 increased in magnitude and significance when using all stocks in Fama & MacBeth (1973) regression. Contrary to the first results, the coefficient on IVOL3 is significant on a 5% level in the later test.

6.2 MAX and Idiosyncratic Volatility Puzzle

One of the possible explanations for the *"iv puzzle"* is documented by Bali *et al.* (2011) who show that the effect of idiosyncratic volatility can be reversed when MAX is included in the Fama & MacBeth (1973) regression. They argue that investors may prefer stocks with extreme previous positive returns because of the upside potential. As stocks with past extreme returns also exhibit higher idiosyncratic volatility, idiosyncratic volatility may appear to be positively priced. However, on the U.S. data sample they show that after controlling for MAX, the effect of idiosyncratic volatility is positive and consistent with the assumption of risk-averse and not fully diversified investors.

I add the MAX variable to the Fama & MacBeth (1973) regression specification and repeat the idiosyncratic volatility puzzle test on all markets that show a significant IVOL3 coefficient. Results are presented in table 6.4.

Table 6.4: MAX, Idiosyncratic Volatility and Future Returns

Country	*Constant*	*MAX*	*IVOL3*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*BM*	*Lagged R*	*Avg. R^2*
Germany	0.759	-0.150	0.232	0.547	0.141	0.340	-0.083	0.190	0.006	0.166
	[2.14]	[-4.36]	[1.76]	[3.77]	[1.28]	[2.90]	[-2.16]	[1.74]	[1.75]	
Italy	1.270	-0.064	-0.406	0.561	-0.061	0.832	-0.103	-0.152	0.006	0.237
	[1.67]	[-1.00]	[-1.04]	[1.86]	[-0.23]	[2.89]	[-1.83]	[-0.27]	[1.33]	
Also not re-	0.954	-0.083	-0.070	0.726	0.167	0.484	-0.143		0.010	0.182
porting BM	[2.82]	[-3.39]	[-0.64]	[2.34]	[1.00]	[2.33]	[-3.54]		[2.31]	
Ireland	-0.084	-0.197	0.482	0.587	0.576	0.177	0.058	0.332	0.018	0.395
	[-0.12]	[-4.48]	[2.75]	[2.00]	[1.53]	[0.34]	[0.67]	[1.66]	[3.30]	
Poland	2.518	-0.105	0.085	1.242	0.258	-0.136	-0.399	0.307	0.025	0.227
	[2.03]	[-2.13]	[0.43]	[2.56]	[0.81]	[-0.37]	[-2.96]	[2.92]	[4.63]	
Spain	-0.321	-0.107	-0.056	0.037	0.598	0.355	0.177	0.554	0.013	0.289
	[-0.60]	[-2.53]	[-0.34]	[0.14]	[3.15]	[1.94]	[2.78]	[4.67]	[3.23]	
Sweden	1.051	-0.168	0.245	0.442	0.167	-0.049	-0.102	0.495	0.001	0.201
	[1.67]	[-5.19]	[1.74]	[2.05]	[0.78]	[-0.24]	[-1.67]	[3.47]	[0.23]	

Notes: Table reports Fama & MacBeth (1973) regressions of monthly excess stock return on MAX - maximum daily return over past month, contemporaneous factor betas, β(MKT), β(SMB), β(HML), size (log market value) and book-to-market at the end of previous month and lagged return over previous 6 months. Reported t-statistics in square brackets are Newey & West (1987) adjusted t-statistics.

With the exception of Italy, all countries exhibit a negative and significant coefficient on MAX. The coefficient on IVOL3 is positive for Germany, Ireland, Poland and Sweden, for Spain, although still negative, it is not significantly different from zero. For Italy coefficients on both MAX and IVOL3 are negative and not significant on a 10% level. However, when stocks also not reporting book-to-market ratio are included in the regression, only the coefficient on MAX remains significant.

In the analysis of U.S. data Ang *et al.* (2009) and Bali *et al.* (2011) use different measures of idiosyncratic volatillity. While Ang *et al.* (2009) estimate IVOL3 using the three-factor model, Bali *et al.* (2011) use simple one-factor model to measure IVOL1. I repeat all regressions using IVOL1 instead of IVOL3 and confirm that the results are robust to the different ways of measuring idiosyncratic volatility.

The above presented results verify that the previous findings of Bali *et al.* (2011) are valid also on European markets and the anomalous relation between lagged idiosyncratic volatility and returns reverses or remains insignificant after controlling for MAX.

6.3 Premium on Lottery-Type Stocks

In the third set of Fama & MacBeth (1973) regressions the underperformance of lottery-type stocks on an individual firm level is investigated. I specify a new dummy variable "LT" and assign value 1 to all stocks that form lottery-type portfolio in section 5.2. Table 6.5 reports the results from regressions of excess returns on lottery-type dummy variable, β factor loadings and firm characteristics.

Markets that exhibit a lower return for lottery-type stocks on an aggregate portfolio level show lower returns also in Fama & MacBeth (1973) regression with the exception of the United Kingdom. In addition, 6 more countries (Belgium, Finland, France, Greece, the Netherlands and Poland) show significant underperformance of lottery-type stocks.

The reason why these countries do not show lottery-type portfolio underperformance on an aggregate portfolio level, but only in Fama & MacBeth (1973) regression can be attributed to equal weightening in Fama & MacBeth (1973) methodology. As lower returns for lottery-type stocks are often associated with small-capitalization companies, the pricing effect is more apparent when equal weightening is used.

Table 6.5: Lottery-Type Stocks and Future Returns

Country	*Constant*	*LT*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*BM*	*Lagged R*	*Avg. R^2*
Austria	-0.335	-0.475	0.068	0.296	0.426	0.113	0.069	0.008	0.297
	[-0.81]	[-1.78]	[0.19]	[0.95]	[1.53]	[1.70]	[1.61]	[1.29]	
Belgium	0.327	-0.644	0.508	0.196	-0.328	-0.046	0.317	0.003	0.276
	[1.14]	[-2.93]	[2.21]	[0.99]	[-1.53]	[-1.03]	[4.24]	[0.57]	
Denmark	-0.300	-0.321	0.352	0.298	-0.106	-0.020	0.857	0.012	0.240
	[-0.64]	[-1.37]	[1.42]	[1.45]	[-0.43]	[-0.34]	[5.17]	[2.43]	
Finland	1.164	-0.748	0.996	-0.160	0.090	-0.204	0.410	0.006	0.255
	[2.61]	[-3.45]	[3.12]	[-0.73]	[0.26]	[-3.23]	[3.30]	[1.37]	
France	1.642	-0.543	0.302	0.240	0.367	-0.218	0.083	-0.003	0.168
	[4.18]	[-3.09]	[1.52]	[1.63]	[2.24]	[-4.23]	[1.72]	[-0.74]	
Germany	0.849	-0.838	0.510	0.140	0.337	-0.130	0.233	0.004	0.151
	[2.61]	[-4.96]	[3.56]	[1.31]	[2.82]	[-3.63]	[2.08]	[1.28]	
Greece	1.849	-0.600	-0.220	0.029	0.384	-0.310	0.313	0.006	0.199
	[1.46]	[-2.71]	[-0.51]	[0.09]	[1.68]	[-2.55]	[2.07]	[1.04]	
Ireland	-0.070	-0.819	0.739	0.480	0.174	0.023	0.459	0.012	0.356
	[-0.14]	[-1.91]	[2.80]	[1.24]	[0.33]	[0.33]	[2.54]	[2.34]	

Country	*Constant*	*LT*	*β(MKT)*	*β(SMB)*	*β(HML)*	*Size*	*BM*	*Lagged R*	*Avg. R^2*
Italy	0.034	-0.082	0.637	0.122	0.660	-0.061	-0.191	0.004	0.217
	[0.08]	[-0.34]	[2.05]	[0.57]	[2.60]	[-1.44]	[-0.32]	[0.74]	
Netherlands	0.562	-0.582	0.614	-0.093	-0.115	-0.032	0.046	0.016	0.265
	[1.64]	[-3.79]	[2.97]	[-0.69]	[-0.58]	[-0.75]	[0.91]	[3.81	
Poland	2.418	-1.662	1.283	0.222	-0.176	-0.449	0.360	0.020	0.211
	[2.14]	[-3.76]	[2.79]	[0.69]	[-0.49]	[-3.55]	[3.09]	[4.21]	
Spain	-0.574	-1.091	-0.000	0.617	0.377	0.145	0.581	0.014	0.270
	[-1.04]	[-5.77]	[-0.00]	[3.20]	[2.08]	[2.44]	[4.49]	[3.56]	
Sweden	0.866	-1.126	0.414	0.131	-0.006	-0.114	0.463	-0.002	0.182
	[1.30]	[-4.75]	[1.91]	[0.65]	[-0.03]	[-1.85]	[3.26]	[-0.30]	
United	0.869	-0.218	0.525	0.298	0.046	-0.161	0.235	0.013	0.100
Kingdom	[2.41]	[-1.47]	[3.66]	[2.08]	[0.58]	[-3.66]	[4.82]	[4.98]	

Notes: Table reports Fama & MacBeth (1973) regressions of monthly excess stock return on LT dummy variable which assigns value 1 to all stocks that form lottery-type portfolio as described in section 5.2, contemporaneous factor betas, β(MKT), β(SMB), β(HML), size (log market value) and book-to-market at the end of previous month and lagged return over previous 6 months. Reported t-statistics in square brackets are Newey & West (1987) adjusted t-statistics

The economic significance of lottery-type stocks underperformance is similar to the results on an aggregate portfolio level. The annual return differences are 7.728% for Belgium, 8.964% for Finland, 6.516% for France, 10.056% for Germany, 7.2% for Greece, 9.828% for Ireland, 6.984% for the Netherlands, 19.944% for Poland, 13.092% for Spain and 13.512% for Sweden.

Compared to other countries, Poland shows the highest underperformance of lottery-type stocks. The reason for this is the shorter sample period beginning only in 1998 for Polish data set as further described in the following section.

6.4 Time-Series Effects

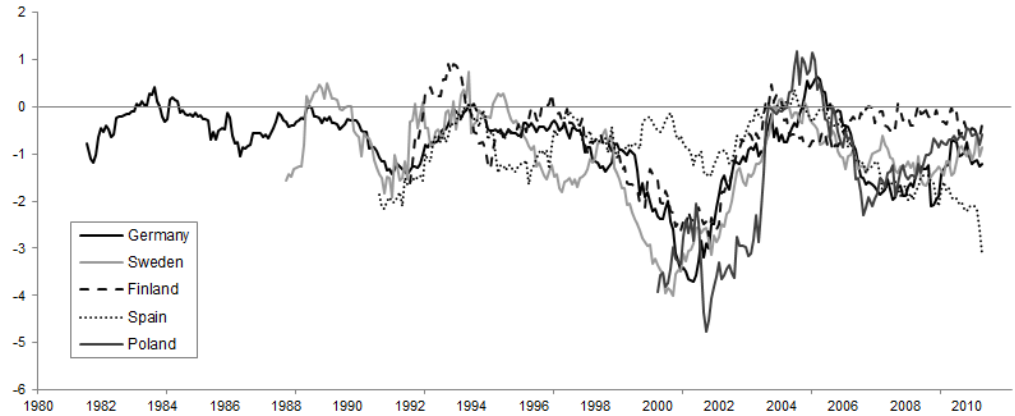
Besides exploring the performance of lottery-type stocks on an individual level, Fama & MacBeth (1973) regressions also allow to investigate the return differentials adjusted for risk and firm characteristics in different time periods.

I want to address the question of whether the underperformance of lottery-type stocks shows any time trend and whether it persists in different time periods. For this purpose the lottery premium at period t is defined as the estimated LT dummy variable coefficient from Fama & MacBeth (1973) cross-sectional regressions described in the previous section. Central moving averages of 24 monthly observations of lottery premium are plotted in figure 6.1. The figure contains five countries with the highest coefficients on LT dummy variable.

The results show that the lottery premium exhibits episodes of increases and decreases with the largest drop during the late 1990's reversed in the early 2000's. More interestingly, the observed episodic phenomenon is common for multiple markets. Especially Germany, Sweden and Poland show very similar time patterns in the lottery premium. Also countries excluded from the figure show a similar decrease in the 1990's, although its magnitude for Belgium, Italy, Greece and Spain is smaller. Results for other countries are reported in appendix A.

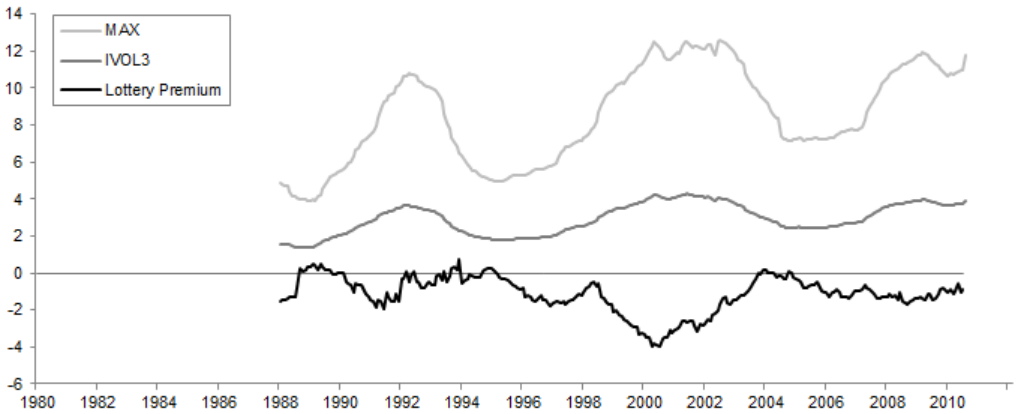
Given the episodic behavior of the predicted lottery premium shown in figure 6.1, a natural question, whether these time-series patterns are related to behavior of lottery characteristics, arises. Figure 6.2 plots the predicted lottery premium and average IVOL3, ISKEW and MAX for the Swedish market. The episodes of a more pronounced lottery premium appear to coincide with episodes of higher idiosyncratic volatility and higher MAX.

Figure 6.1: Lottery Premium Time Series



Notes: Figure displays 24 month central moving averages of lottery premium in percentages defined as the coefficient of LT lottery-type dummy variable from Fama & MacBeth (1973) cross-sectional regressions for five countries with the highest lottery premium.

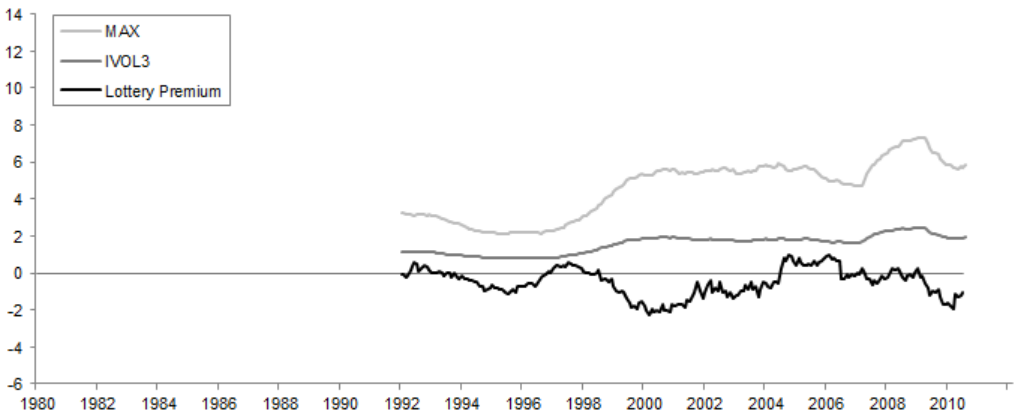
Figure 6.2: Sweden - Lottery Premium and Lottery Characteristics



Notes: Graph displays 24 month central moving averages of lottery premium, average IVOL3 and average MAX for Swedish stock market. Lottery premium is defined as the coefficient of LT lottery-type dummy variable from Fama & MacBeth (1973) cross-sectional regressions.

Figure 6.3 plots a time-series of lottery premium and lottery characteristics for Austria, a country that does not exhibit significant lottery premium. Compared to Sweden, the episodic behavior of both idiosyncratic volatility and lottery premium is less pronounced. Additionally, the average levels of idiosyncratic volatility and MAX are lower compared to Sweden.

Figure 6.3: Austria - Lottery Premium and Lottery Characteristics



Notes: Graph displays 24 month central moving averages of lottery premium, average IVOL3 and average MAX for Austrian stock market. Lottery premium is defined as the coefficient of LT lottery-type dummy variable from Fama & MacBeth (1973) cross-sectional regressions.

These results suggest a possible explanation that the lottery premium has a higher magnitude during speculative periods when both idiosyncratic volatility and maximum daily returns are high. The predicted lottery premium is also more pronounced on markets that exhibit higher IVOL3 and MAX, and are therefore possibly more affected by the speculative periods. The episodic behavior of lottery premium is shared across multiple markets, especially the large swing in the late 1990's.

Kumar *et al.* (2010) suggest that the episode of speculative trading by retail investors can explain the increase in idiosyncratic volatility observed on the U.S. stock market in the late 1990's documented by Campbell *et al.* (2001). The increase in speculative trading could cause both higher idiosyncratic volatility and higher pricing of lottery-type stocks observed on European markets and therefore the suggested explanation is consistent with time patterns of lottery premium presented above.

Chapter 7

Lottery Premium and Propensity to Gamble

One natural question when studying propensity to gamble in stock markets is whether this propensity is correlated to the propensity to gamble in other fields such as state lotteries, casinos and other games. Previous research presented by Kumar (2009) and Kumar *et al.* (2011b) shows that both individual and institutional investors located in U.S. regions with a higher propensity to gamble, hold proportionally more stocks featuring lottery characteristics. A similar comparison on European stock markets is limited by several factors.

First, proxies used in U.S. studies for propensity to gamble are not good proxies in Europe. As documented by Kumar *et al.* (2011b) U.S. counties, which are less religious and are more Catholic, exhibit higher lottery sales and have a higher propensity to gamble. Europe has a different history of church and lotteries and does not show the same pattern. For example, several Protestant countries, the United Kingdom, Sweden and Finland exhibit higher gross revenues from the gaming industry reported in table 7.1. Similarly, gross gaming revenue is higher in Finland and Ireland, which have also higher levels of religiosity. For this reason I proxy the country gambling propensity by gross gaming revenue published by Swiss Institute of Comparative Law (2006).

Second, as the number of stock markets with sufficient number of stocks is limited, also the number of data points for countries is limited. This leads to less efficient research design and may lead to biased inferences. Nevertheless, a less aggregate level of research is not possible without data on individual investor trades, which are not easily accessible.

Third, while lottery markets are quite local, dominated by residents of a

country, stock markets have a considerable proportion of foreign investors. At the end of 2007 European listed companies were 37% owned by foreign investors (Federation of European Securities Exchanges 2008). On the other hand, individual investors show a preference for local companies, the so-called home bias. Karlsson & Norden (2007) document that home bias is more pronounced in the case of less wealthy men who were also found to have a higher propensity to gamble in stock markets by Kumar (2009). Bailey *et al.* (2008) confirm these findings but in addition document that individual investors who hold foreign stocks often use foreign investment for speculation and prefer volatile small-cap stocks. Therefore the pricing pattern of lottery-type stocks is not necessarily caused by local investors.

Finally, as documented in the previous chapter, lottery premiums in stock markets show episodic behavior while the variation in lottery sales is much smaller. For this reason lottery premiums are estimated over a period where they show similar increase reversed by decrease in magnitude for all countries. I compare lottery premium estimated over July 1998 to December 2003 to gross gaming revenue (GGR) per capita for the year 2003. Results are plotted in figure 7.1 and displayed in table 7.1.

Figure 7.1: Lottery Premium and Gross Gaming Revenue

Notes: Figure plots estimated lottery premium on gross gaming revenue per capita. Darker points represent countries with lottery premiums not significantly different from zero, lighter points represent countries with significant lottery premium on 10% level. Lottery premium is defined as the coefficient of LT lottery-type dummy variable from Fama & MacBeth (1973) cross-sectional regressions.

The most evident outlier in figure 7.1 is Poland, which has the highest

lottery premium and the lowest gross gaming revenue per capita. The group of countries with small lottery premiums show a negative relation between GGR per capita and lottery premium, however this relation is not so apparent for countries with significant lottery premium.

Table 7.1: Country Gaming Propensity Statistics

Country	*GGR Per Capita*	*GGR/GDP*	*Lottery Premium*	*t-statistic*
Austria	0.110	0.397	-1.315	[2.75]
Belgium	0.066	0.246	0.076	[0.13]
Denmark	0.154	0.440	-1.341	[-2.57]
Finland	0.238	0.853	-1.673	[-3.37]
France	0.123	0.479	-0.791	[-1.13]
Germany	0.102	0.392	-1.825	[-3.49]
Greece	0.097	0.619	-0.378	[-1.21]
Ireland	0.288	0.811	-1.290	[-1.63]
Italy	0.108	0.462	-0.564	[-1.67]
Netherlands	0.127	0.433	-0.924	[-1.67]
Poland	0.011	0.226	-3.150	[-3.69]
Spain	0.117	0.624	-0.621	[-1.84]
Sweden	0.177	0.568	-2.513	[-3.87]
United Kingdom	0.185	0.666	-0.688	[-1.48]

Notes: Table presents gross gaming revenue (total revenue minus winnings) per capita and GDP for year 2003 based on Swiss Institute of Comparative Law (2006). Lottery premium is defined as a coefficient on LT dummy variable in Fama & MacBeth (1973) regressions estimated over period July 1997 - December 2003. T-statistics are reported in square brackets.

Regression of predicted lottery premiums on gross gaming revenue per

capita, after excluding Poland as an outlier, presents a negative coefficient on GGR per capita (-5.255) with a t-statistic of -1.79. This result, significant on a 10% level, suggests that the gambling propensity in the gaming industry could be correlated with the gambling propensity on stock markets.

7.1 Robustness Checks

As the small number of data points can easily lead to biased inferences I conduct additional tests to ensure that the results are robust. First I re-estimate the lottery premium using an alternative proxy for lottery-type stocks. I create MAXdummy and assign value 1 to all stocks in the highest MAX decile in each month. An alternative MAX-lottery premium is then measured using MAXdummy variable in the Fama & MacBeth (1973) regressions over the same period from July 1998 until December 2003.

Second, I ensure that the results are robust to the proxy used for gambling propensity. I repeat the regression using gross lottery revenue per capita (GLTR PC). This variable measures only gross gaming revenue from lotteries, excluding casinos, slot machines, bingos and betting. Finally I use gross gaming revenue divided by GDP.

Since Ireland is the only country for which stocks listed on foreign stock exchange are included in the data sample, I repeat all tests excluding also Ireland. Results from robustness checks are reported in the table 7.2.

All regressions show negative relation between the lottery premium and the gambling propensity proxy. When using gross lottery revenue, the coefficients are even significant on a 5% level. On the contrary coefficients on gross gaming revenue/GDP are not significant on any conventional level for LT-lottery premium, although they remain significant on a 10% level for MAX-lottery premium.

Overall, the above results provide some evidence, although not strong, that countries with a higher propensity to gamble show a higher lottery premium in stock markets.

Table 7.2: OLS Regressions - Lottery Premium on GGR

Dependent Variable	*Independent Variable*	*Coefficient*	*t-statistic*	$P > \|t\|$
Excluding Poland				
LT-Lottery Premium	GGR PC	-5.267	-1.79	0.100
	constant	-0.297	-0.64	0.534
MAX-Lottery Premium	GGR PC	-27.098	-1.75	0.107
	constant	3.319	1.36	0.200
LT-Lottery Premium	GLTR PC	-22.061	-2.41	0.035
	constant	0.292	0.50	0.628
LT-Lottery Premium	GGR/GDP	-0.107	-0.92	0.375
	constant	-0.490	-0.76	0.465
MAX-Lottery Premium	GGR/GDP	-1.076	-2.01	0.070
	constant	5.160	1.71	0.115
Excluding Poland and Ireland				
LT-Lottery Premium	GGR PC	-8.578	-2.16	0.056
	constant	0.102	0.18	0.858
MAX-Lottery Premium	GGR PC	-39.214	-1.81	0.100
	constant	4.779	1.56	0.149
LT-Lottery Premium	GLTR PC	-21.936	-2.28	0.046
	constant	0.291	0.47	0.645
LT-Lottery Premium	GGR/GDP	-0.113	-0.83	0.428
	constant	-0.461	-0.63	0.546
MAX-Lottery Premium	GGR/GDP	-1.182	-1.86	0.092
	constant	5.622	1.65	0.130

Notes: Table reports estimates from OLS regressions of lottery premium on gaming propensity proxies. Lottery Premium is measured by Fama & MacBeth (1973) regressions using LTdummy (LT-Lottery Premium) or MAXdummy (MAX-Lottery Premium) with value 1 for stocks in the highest MAX decile. GGR PC denotes gross gaming revenue per capita, GLTR PC is gross lottery revenue per capita, GGR/GDP is gross gaming revenue divided by GDP. Lottery Premiums are estimated over period July 1998 - December 2003. Gaming data are for the year 2003.

Chapter 8

Conclusion

Kumar (2009) documents that stocks that appear to be like lotteries gain lower future returns. Bali *et al.* (2011) suggest that a preference for lottery-type stocks can explain the negative anomalous relation between idiosyncratic volatility and returns, the so called *"iv puzzle"*, documented by Ang *et al.* (2009) on both the U.S. and European markets.

I present new evidence related to these previous findings from 14 European countries. In European markets stocks with lottery characteristics tend to have lower returns. This underperformance is both statistically and economically significant and is most pronounced in Germany, Spain and Sweden. Italy and Austria do not show underperformance of lottery stocks when measured over the whole sample period. Nevertheless both countries exhibit episodes of lower returns associated with lottery-type stocks in the late 1990's and early 2000's.

Periods in which the cross-sectional estimate of lottery premium is most significant and negative coincide with periods of high average idiosyncratic volatility and high maximum daily returns. A possible interpretation of this relation is that the episodic behavior of lottery premium and lottery characteristics corresponds to speculative periods when retail investors find stocks featuring lottery characteristics more attractive.

Besides documenting the pricing implications of lottery characteristics, I assess the question whether preference for lottery-type stocks can help explain the *"iv puzzle"*. Firstly, I find that the previous results presented by Ang *et al.* (2009) are not robust to the sample period and inclusion of stocks not reporting book-to-market ratio. In the extended data set the anomalous negative relation between lagged idiosyncratic volatility and returns is significant only in Germany, Italy, Ireland, Poland, Spain and Sweden. Moreover, on all six

markets this negative relation reverses or remains insignificant after controlling for lagged maximum daily returns. This is to my best knowledge the first time the Bali *et al.* (2011) finding is verified on broad set of markets.

Finally, the original results of this study show that the propensity to gamble in stock markets appears to be correlated with the propensity to gamble in lotteries and other games. These results suggest that the occurrence and impact of risk-seeking behavior in stock markets might be more relevant than currently perceived. Further research on a less aggregate level could examine preferences for lottery-type stocks using data on individual investor trades and investigate what are the economic sources of episodic behavior of the lottery premium.

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Appendix A

Time-Series Plots

Following figures display 24 month central moving averages of lottery premium, average IVOL3 and average MAX. Lottery premium is defined as the coefficient of LT lottery-type dummy variable from Fama & MacBeth (1973) regressions.

Figure A.1: Belgium - Lottery Premium and Lottery Characteristics

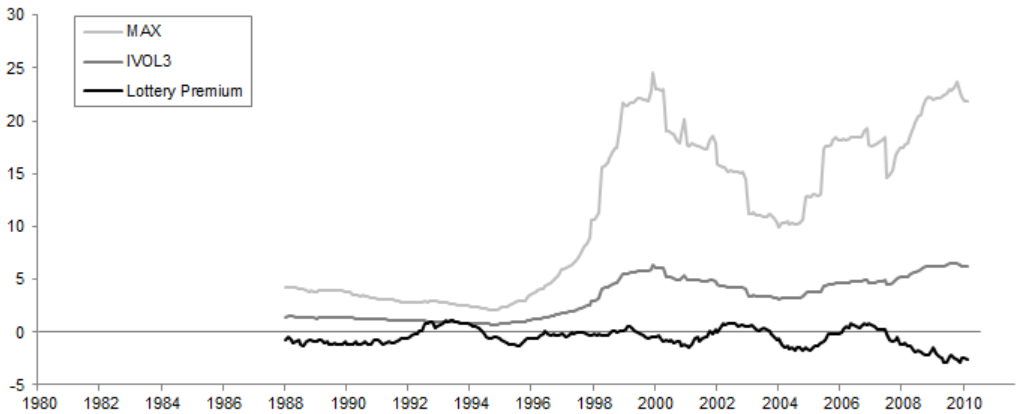

Figure A.2: Denmark - Lottery Premium and Lottery Characteristics

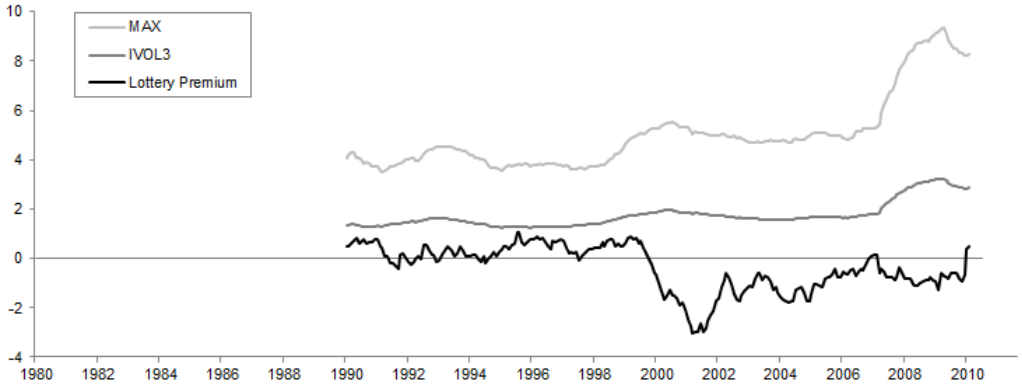

Figure A.3: Finland - Lottery Premium and Lottery Characteristics

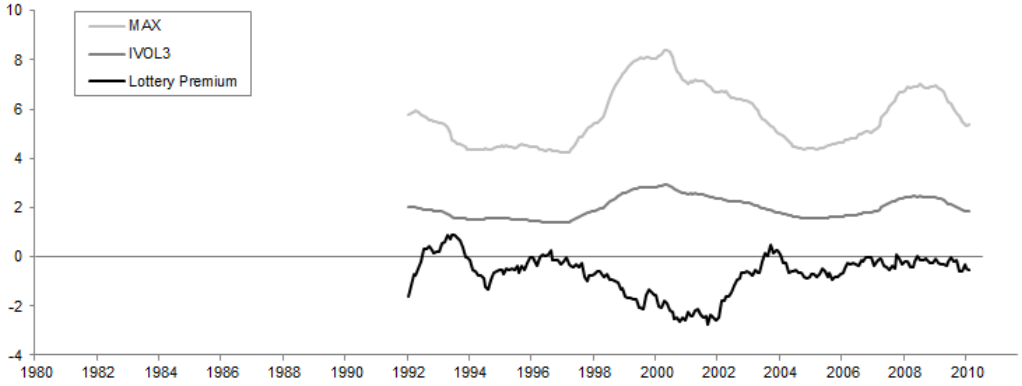

Figure A.4: France - Lottery Premium and Lottery Characteristics

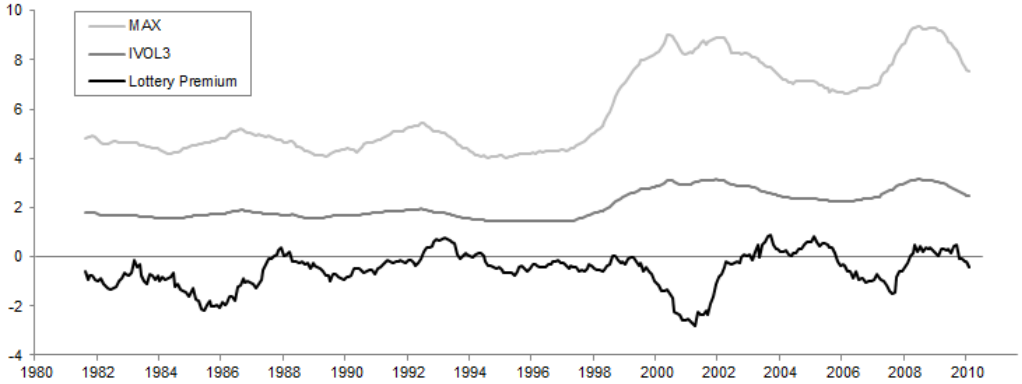

Figure A.5: Germany - Lottery Premium and Lottery Characteristics

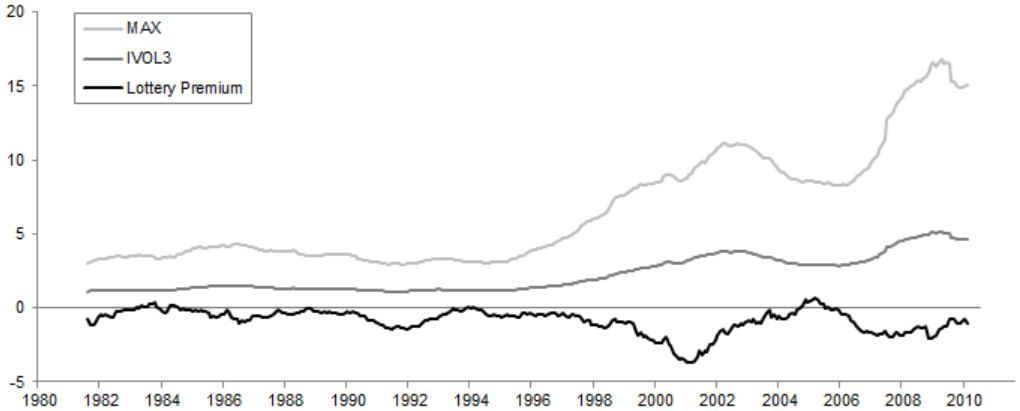

Figure A.6: Greece - Lottery Premium and Lottery Characteristics

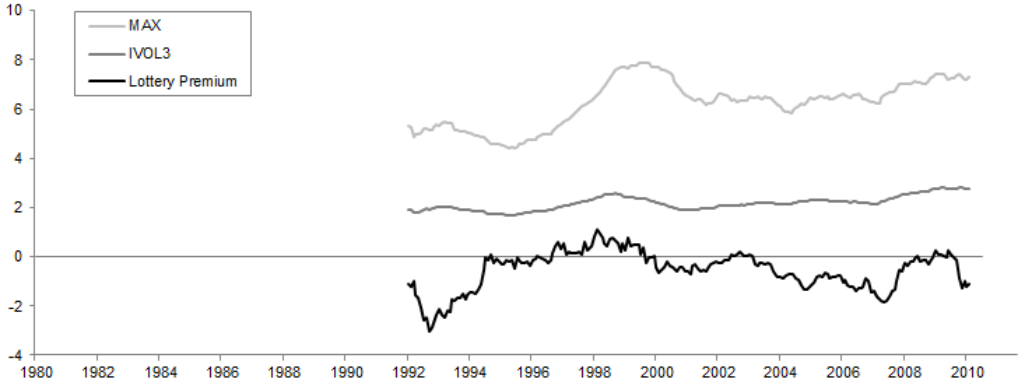

Figure A.7: Ireland - Lottery Premium and Lottery Characteristics

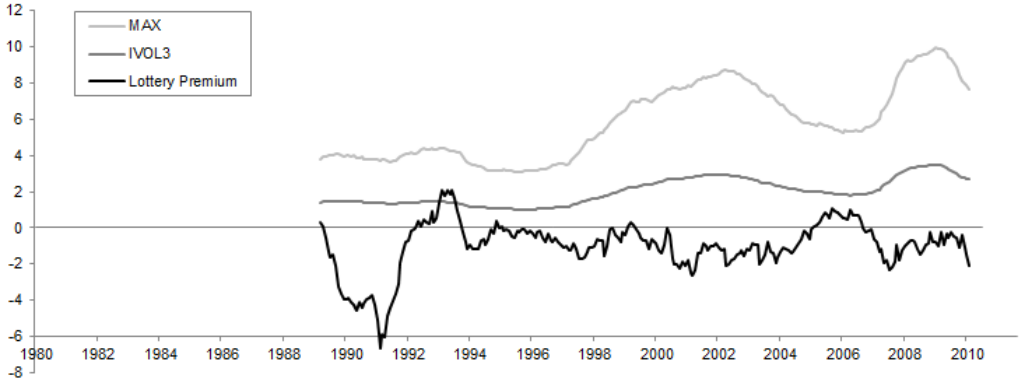

Figure A.8: Italy - Lottery Premium and Lottery Characteristics

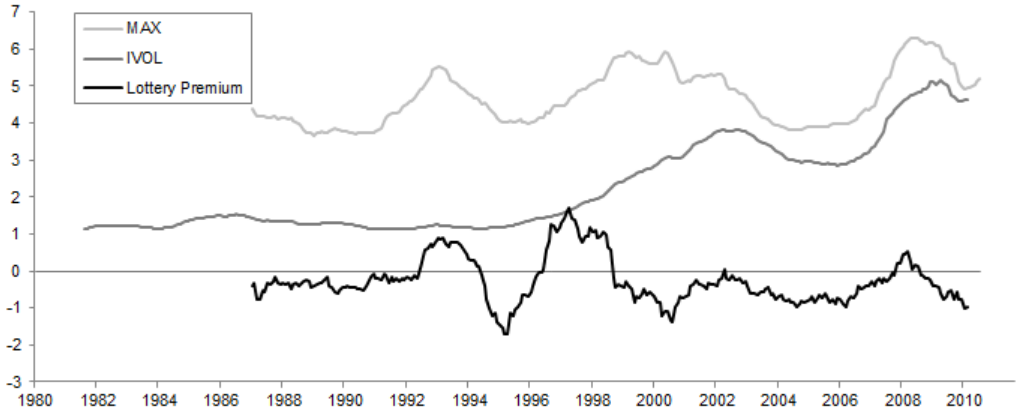

Figure A.9: Netherlands - Lottery Premium and Lottery Characteristics

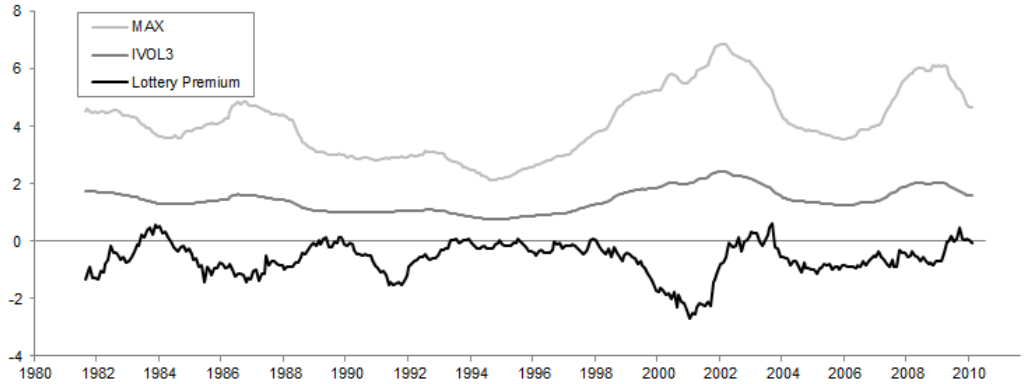

Figure A.10: Poland - Lottery Premium and Lottery Characteristics

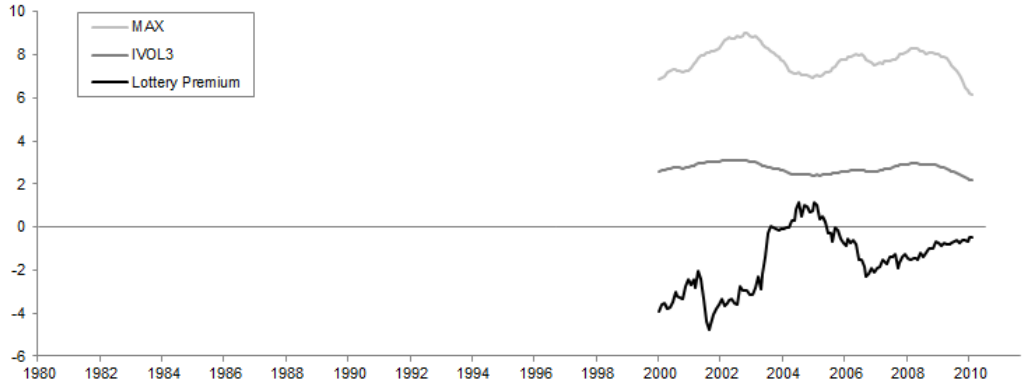

Figure A.11: Spain - Lottery Premium and Lottery Characteristics

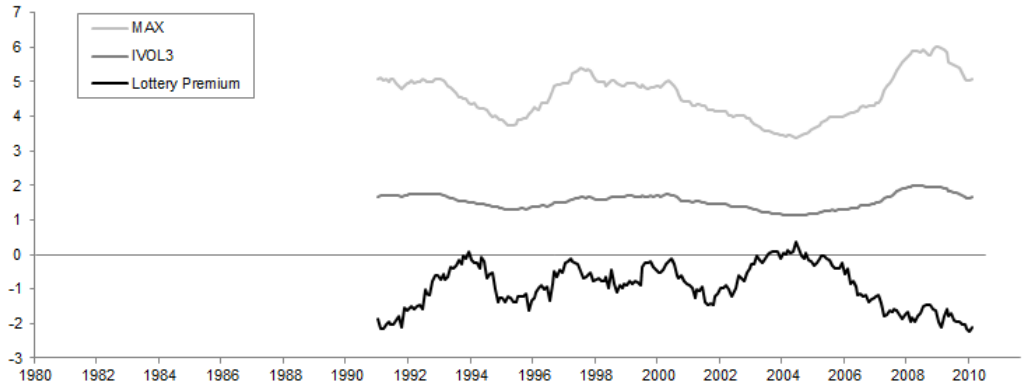
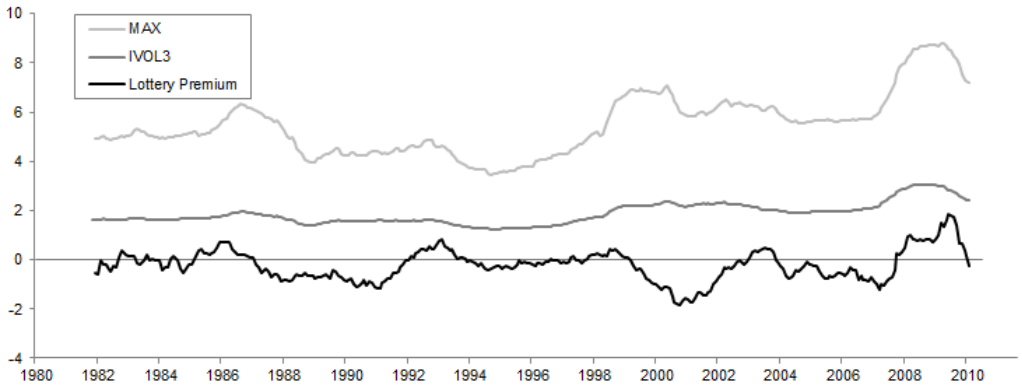
Figure A.12: United Kingdom - Lottery Premium and Lottery Characteristics