Hoping for the jackpot

Swedish individual investors' trading activities in lottery stocks

Krisztián Pintér 40394 **Johannes O. Koblitz 40403**

Department of Finance
Stockholm School of Economics

Abstract

In this thesis we analyze behavioural biases that can affect Swedish individual investors during the first years of the financial crisis, between January 2006 and January 2009. In particular, we examine their trading activity of lottery stocks and its effect on the prices, and consequently, on the returns of these stocks. Firstly, we show that Swedish individual investors have a preference towards lottery stock features, such as low price, high idiosyncratic skewness, and high idiosyncratic volatility. Secondly, our results indicate that there is a negative relationship between stock market movement and preference by individuals towards lottery stocks that incorporate all these three characteristics. This means when the market performs poorly, individuals' propensity to gamble increases and they excessively net-buy lottery stocks. Thirdly, we show that individuals are noise traders in lottery stocks. Due to their large trading activities in lottery stocks they are able to drive up the price of these stocks in the short term, which may result in low expected returns in the middle and long term. Since the lottery stock portfolio underperforms the non-lottery portfolio in the middle and long term, investors are worse off by investing in lottery stocks. Finally, we argue that for a time horizon of 12 months a long-short arbitrage strategy to trade against these noise traders is risky and involves substantial costs.

Keywords: Behavioural finance; lottery stocks; idiosyncratic skewness; idiosyncratic volatility; noise trading

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1. Introduction

Before the 2007 financial crisis the prevailing view in finance and economics was that markets are semi-strong efficient[2] (Fama, 1970), individuals are all rational and make their (investment) decisions based on thorough research and fundamental analysis. This view implies that individuals' investment decisions are not affected by any behavioural bias, and not driven by emotions or feelings. This efficient market hypothesis states that the market is always right due to its self-correcting mechanism. This efficient market paradigm assumes, as a first approximation, that individuals are rational. But even if some of them are not rational and they make investment mistakes, The decisions of these individuals are random which means that they not correlated with each other. However, in such a case if these mistaken investment beliefs are correlated and would be strong enough to move prices, arbitragers step in and correct the market and push back the price to its fundamental value.

However, this crisis shed light once again on the irrational behaviour of financial market participants and on the failure of the efficient market hypothesis. Consequently, since then more and more attention has been focused on the field of behavioural finance. This area has been active for several decades now, but has become more influential only in the last 20 years. The main arguments of behavioural finance can be summarized as the following (Shiller, 1998; and Barberis and Thaler, 2003): (1) individuals are many times irrational, and affected by several behavioural biases, and heuristics, (2) the irrational behaviour of individuals is many times correlated with each other and can have an upward or downward pressure on stock prices, (3) markets are not totally self-correcting because arbitrage is many

[2] prices reflect all publicly available information (no profit from trading around specific events)

times too risky or costly and therefore arbitrageurs do not eliminate mispricing, and (4) it is difficult to determine what is the fundamental, rational value of an asset that we use as a benchmark to compare irrational behavioural to on the first place.

Behavioural finance has several different fields, which try to understand various forms and causes of irrational behaviour. These fields include the investigation of heuristics, moods, and the creation of bubbles in financial markets, just to mention a few.

Research so far has established two main individual investor biases, underinvestment and excessive trading (Barberis and Thaler, 2003) that have a negative effect on the wealth and the portfolio return of individuals. Prospect theory and cumulative prospect theory (Kahneman and Tversky, 1979 and 1992) shed light on some other important biases as well. One of these is that individuals have a preference for positive skewness, because they overweight low probabilities, and underweight medium probabilities. Furthermore, these theories argue that when investors are in the domain of losses, they become risk-seeking and are more willing to accept gambles which they would reject in normal times. These biases can easily lead individuals to follow unprofitable trading strategies.

Nonetheless, extensive research in the field of individuals' irrational investment behaviour, has not been done so far , especially not in such a recent time period as the current financial crisis.

Therefore, one of our objectives in this paper is to understand better Swedish individuals' preference for positive skewness and the effect of the misperception of probabilities on their returns at the beginning of the financial crisis in the period between January 2006 and January 2009. We will observe this phenomenon through lottery type stocks on the Swedish market. We will analyze whether Swedish individual investors indeed have a preference for positive (idiosyncratic) skewness and for other characteristics that typically describe lottery-type stocks (such as low price and high idiosyncratic volatility), because this research, to the best of our knowledge, has been done so far only for other countries, especially focusing on the U.S.

After we have established this preference, we are interested in whether individuals are more prone to buy lottery-type stocks, that compound the previously mentioned characteristics, in times of bad market performance, as prospect theory would suggest.

As a next step we will focus on the effect of excess net buy of these stocks by individual investors, whether they are able to move, and have an upward pressure on the price of lottery stocks. As a last point in this line of arguments we will analyze whether a portfolio composed of lottery stocks underperforms a portfolio of non-lottery stocks, as it is shown by some previous research in the U.S. market.

Another main objective of this paper is to understand the effect of the mispricing of lottery stocks caused by these noise trader individuals and analyse whether arbitrageurs can step in and self-correct the market. We will show whether the arbitrage strategy would be too costly and risky which would make arbitrageurs shy away from trading aggressively against these stocks. This would leave the price at a level that is different from its fundamental value, and this would prove the failure of the efficient market hypothesis.

The remainder of the paper is organized as follows: in section 2 the methods and theories used in our paper will be presented, including summaries of previous research that has incorporated them; then in section 3 we give further reasons for the choice of our topic and state our four hypothesis; in section 4 we present the data sets we use in our analysis; in section 5 we present and analyze the results of our calculations; and finally, we conclude our findings in section 6.

2. Theoretical background

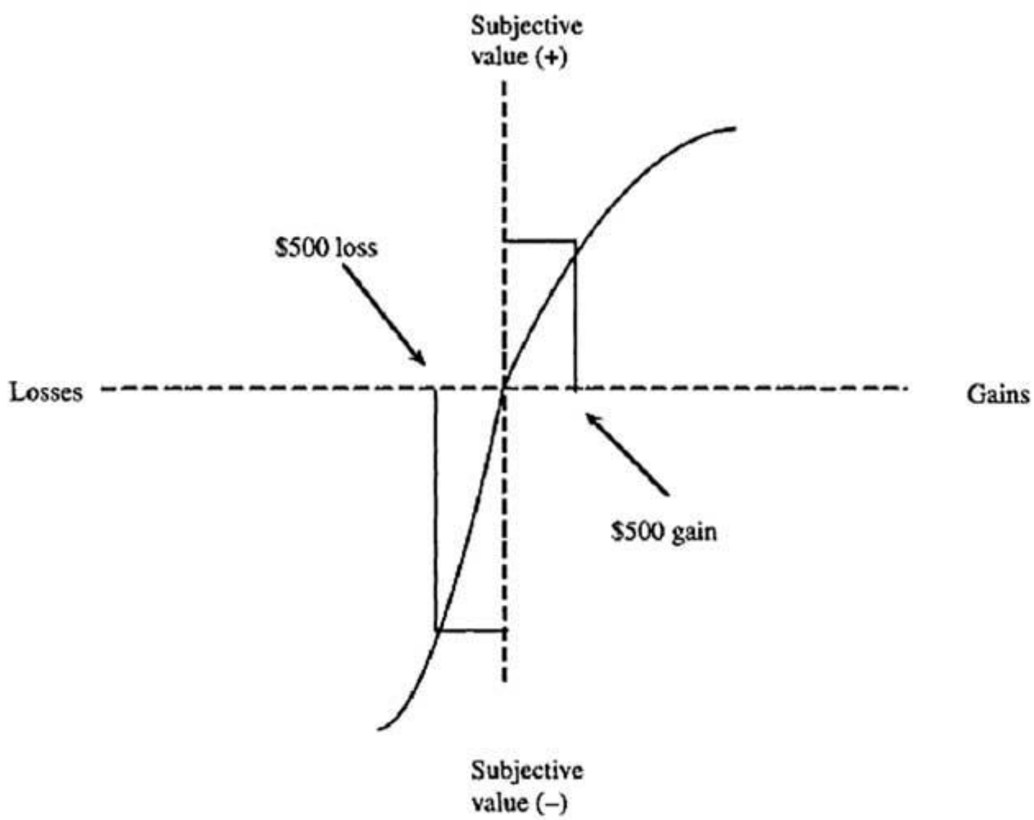
2.1. Prospect theory

The 2007 financial crisis once again has shown that investors do not behave in such a rational and predictable way as it was assumed by most of the traditional financial and economic theories. Consequently, academia's focus has increased on research about investors' mood and irrationality of individual investors that might drive prices in markets all over the world. Furthermore, theories as the prospect theory (Kahneman and Tversky, 1979), that builds on the individuals' different perception of gains and losses, and on the irrationality of investors, came to the spotlight again.

Based on the expected utility theory, which preceded the prospect theory, investors are fully rational, and when they make investment decisions, they rationally weight the expected payoffs and choose the investment with the highest expected payoff. In this world, people are like machines and their investment strategies are not influenced by any feelings and emotions. They are all well-informed, experienced, and professional actors in the market, without any biases that might affect them. However, already before the 2007 financial crisis, researchers realized that the world does not exactly work as it is described by the expected utility theory. The result of this recognition led to the formulation of the prospect theory. According to this theory, when people are facing decisions with unknown future outcomes, they are not always calculating a rational, weighted average of the expected payoffs. Rather, they put bigger weights for losses than for gains. The reason is that a loss hurts more than an equivalent gain creates utility. Furthermore, the theory argues that investors are risk-averse when they are in the domain of gains, while risk-seeking when they are in the domain of losses, because they are willing to take extra risk in order to at least break-even and not to lose money. Built on the irrationality derived from prospect theory, researchers have focused on trying to understand the behavioural biases that affect investors, such as overconfidence, representativeness and availability heuristic, anchoring, etc. (Shiller, 1998).

Figure 1 - Utility function in prospect theory
(Kahneman and Tversky, 1979 and 1992)

The figure shows the size of utility individuals derive from a given ($500) gain and loss. The utility line of loss is much steeper than that of gain, which means that a loss has a bigger negative effect on utility than an equivalent gain has positive effect.



2.2. Sentiment, mood, and other biases

In order to understand better the effects of these biases and the behavioural aspect of investments, during the last decade several research has been done that try to find relations between investor's mood and stock market behaviour. According to Loewenstein (2000) feelings are important at the time of making an investment decision, because they "often propel behaviour in directions that are different from that dictated by a weighting of the long-term costs and benefits of disparate actions".

Other researchers were focusing on effects on the stock market such as no secular holidays (Frieder and Subrahmanyam (2004)), and Hirshleifer and Shumway (2003)).

Kaplanski and Levy (2010) examine the effect of aviation disasters on the stock market. They find that the fear, anxiety, and negative sentiment due to the disasters causes short-term decline in the stock market (for about 2 days); however, after the first shocking days the market moves back to its original level.

Lepori (2010) studies the opposite sentiment to that observed by Kaplanski and Levy. Therefore, he examines what happens when people are in good mood. For the research he uses comedy movie releases at weekends in the U.S. as proxy for good mood, and observes what happens on the following Mondays. He finds that the more comedy movies are released during the weekend, the bigger the drop in the stock market on the subsequent Monday. He finds the effect to be bigger for high volatility stocks.

Dowling and Lucey (2003) examine no less than eight proxy variables for investors' mood (based on weather, biorhythms, and beliefs) and study their effect on the Irish stock market. However, only two of them, the rain and the Monday variable (the hypothesis that on Mondays the stock market performs worse than on other days), are both economically and statistically significant.

Since many of these behavioural biases affect individual investors more than institutional investors due to their lack of financial literacy (Stango and Zinman (2011), Alessie, Van Rooij, and Lusardi (2007), Lusardi and Mitchell (2008), Lusardi and Tufano (2009), and Barrot (2011)), there is an expanding literature that focuses on individual retail investors.

Dorn, Huberman, and Sengmueller (2006) find that (German) retail investors even trade in tandem, so that their correlated market orders lead returns. Furthermore, their investments are governed mainly by speculative motives. Kumar, Page, and Spalt (2010) follow the same line, by stating that these comovements are stronger among stocks that have lottery features; and are amplified during periods of greater market-level uncertainty and stronger consumer sentiment.

Chiang, Qian, and Sherman (2009) analyze the IPO market in Taiwan. They find that the involvement of individual investors as a group is heavily determined by recent performance. This leads to return-chasing behaviour, which means that "they are more likely to enter an auction if returns on recent auctions have been high". Due to the fact that these investors are uninformed and systematically overbid, the authors even pose the question whether individual investors have the necessary sophistication to participate in pricing such highly risky securities as IPOs.

Furthermore, Benselinck, Heyman, and Pronk (2010) and Barber and Odean (2008) showed that due to the low capacity and knowledge of individual investors to analyze all kind of stocks, these investors especially gravitate towards attention grabbing stocks (stocks that are in the news, which have abnormal trading volumes, and extreme one-day performance).

2.3. Lottery stocks

One of these attention-grabbing stocks is the lottery-type stock. This is a special group of stocks, whose main characteristic is a low probability of very high return, but high probability of very low return. Most of the time these stocks have very low expected returns and even negative expected excess returns. More precisely, researchers usually characterize these stocks with low price, high (idiosyncratic) positive skewness, and high (idiosyncratic) volatility. These can be regular stocks or IPO stocks. Also options are considered as lottery assets. Often lottery type stocks include stocks of companies from the energy, mining, financial services, bio technology and technology sector.

Dorn and Sengmueller (2012) showed that lotteries and lottery-type stocks have similar features and can even be used as substitutes to each other. They find that the bigger the lottery prize, the less individual investors will trade these kinds of stocks.

An important aspect of these stocks is that individual investors have a preference for positively skewed assets (Barberis and Huang (2007), Mitton and Vorkink (2007), Kumar, Page, and Spatt (2011)) which will soon lead to an overpricing. Due to their price premium positively skewed stocks will underperform in the following year compared to stocks that are not positively skewed. This phenomenon has been shown by Hvidkjaer (2006), Boyer, Mitton, and Vorking (2009), Blau, Bowles, and Whitby (2013), and Kausar, Kumar, and Taffler (2013).

Lutz (2012) was able to construct an index for investor sentiment by the aggregation of returns on lottery-type stocks. This index fits very well the stock market movement and shows an asymmetric relationship between sentiment and market returns: "during bear markets, high sentiment predicts low future returns for the cross-section of speculative stocks and the market overall while the relationship during bull markets is weak and often insignificant".

Several researchers tried to find an answer why people trade so much and buy lottery tickets and lottery-type stocks, when all of these are a negative-sum game. Rydqvist (2011) for example, tried to analyze why investors invest in (Swedish) lottery bonds and what they can gain from that. However he failed to analyse why investors invest in certain lottery bonds and drive their prices.

Several researchers argue that the reason has to do with emotions and feelings. They argue that investors and especially individual investors are very much influenced by such emotions as risk seeking, aspiration, hope, fun, fear, and regret (e.g., Statman (2002), Shefrin and Statman (1985)).

Another explanation is that many people are status-seeking individuals, who want to reach a higher social class, and buying lottery and lottery-type stock is an "easy" and sometimes the only way for these individuals to reach their dream (e.g., Statman (2002), Friedman and Savage (1948), Brenner (1983), Becker, Murphy, and Werning (2000), Dorn and Sengmueller (2009)). Also Kahneman and Tversky (1979) in their prospect theory argue that people prefer lottery and lottery-type stocks not because they like risk, but because that is (maybe the only one) an option for them to move to a higher social class or to get out of poverty. They mention, that "people accept lottery-like odds when their lives are below their levels of aspiration but reject such odds when they are above their levels of aspiration." This means that these individual investors accept gambles in the domain of losses, that, otherwise, in the domain of gains, they would reject.

This effect is especially useful to explain the trading behaviour of individual investors in lottery stocks during different market situations. At times when the market returns are negative, people tend to find the low probability of a large gain of these stocks more attractive than in normal times. In fact, individual investors even think that they are smarter than anyone else and they can pick the stocks with the best and highest odds compared to others. This bias is called the illusion of control (Langer 1975) and leads to another one called overconfidence. Because individuals are so confident in their ability to pick the right stocks, they will overestimate the future performance of their investments relative to the market (Moore, Kurtzberg, Fox, and Bazerman (1999)).

Kumar (2009) extensively analyzed U.S. individual investors through a retail broker and especially focused on their investments in lottery-type stocks. He tried to analyse the socio economic groups which are particularly interested in these stocks, and the time periods when these stocks are most popular. Despite the lack of a precise definition of lottery-type stock, he designed a reasonable selection procedure for these stocks; consequently, most of the researchers of lottery stocks after this paper used his definition. According to him lottery stocks are those which have the lowest price, among them those which have the highest idiosyncratic positive skewness, and among them those which have the highest idiosyncratic volatility. Furthermore, he finds that lottery stocks can be characterized by the following features: low market capitalization, low institutional ownership, relatively high book-to-market ratio, lower liquidity, younger (mean age is about 6 years), low analyst coverage, and mostly no dividend paying.

According to his reasoning for the selection of the three lottery characteristics, individuals are attracted to cheap bets, therefore, they prefer low price stocks. Within that universe of stocks, individuals are attracted to high stock specific skewness, which means low probability of high return while high probability of very low return, which are typical characteristics of lotteries in general. Finally, among the remaining stocks, individuals are more attracted to high stock specific volatility, because this would ensure that the extreme returns observed in the past due to the high idiosyncratic skewness were not just one-time events and they will occur again in the future.

His findings show that individuals are particularly interested in lottery-type stocks. Furthermore, the demand for these stocks increases when the economy performs badly. Additionally, as it was mentioned earlier, these stocks tend to underperform compared to other stocks; consequently, the bigger weight individuals assign to these stocks, the greater the underperformance of their portfolio will be on average. He also finds that these stocks are especially popular among similar socioeconomic clienteles: poor, young, relatively less educated, single men, who live in urban areas, belong to specific minority, and religious (especially Catholic) are more prone to invest in lottery-type stocks. Dorn and Sengmueller (2009 and 2012) found the same about the socioeconomic groups in their research.

Furthermore, in accordance with previous research, Kumar (2009) finds that the weight of lottery-type stocks in individual investors' portfolio is much larger (3.74%) than in that of institutional investors' (0.76%).

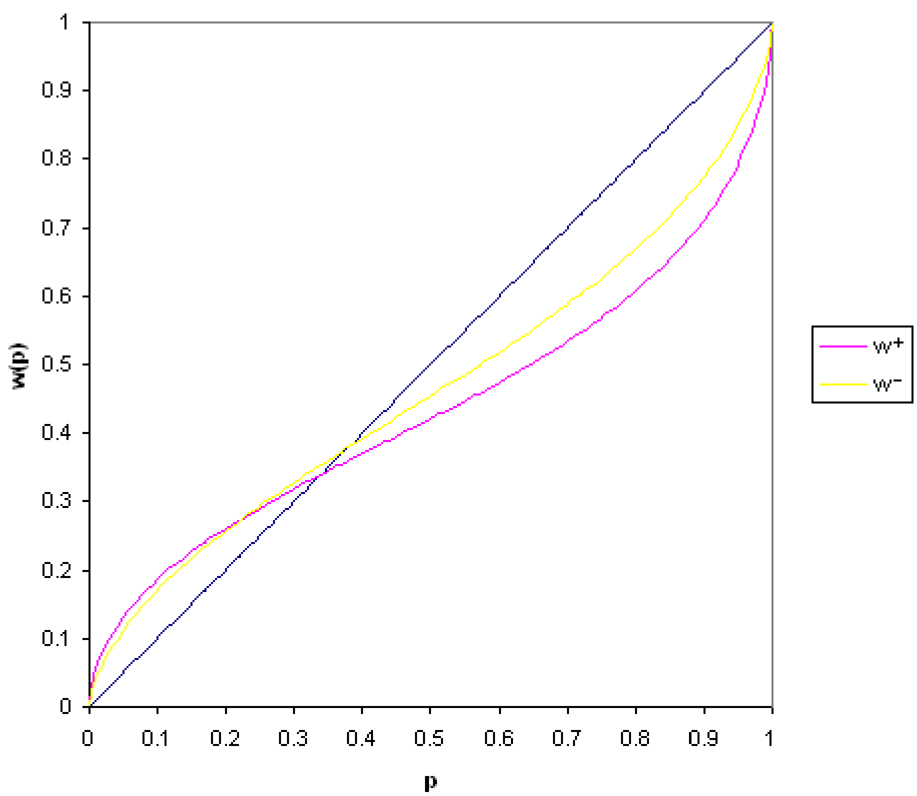
2.4. Cumulative prospect theory

Barberis and Huang (2007) argue that low price positively skewed assets are many times overpriced, because individuals overweight their low probabilities of high return, and therefore want to have these stocks in their portfolio and are willing to pay more for this exposure. As a consequence, this has an upward price pressure on these stocks and results in lower expected returns. Furthermore, individuals are not interested in systematic average skewness, they want to get exposure to the stock specific idiosyncratic skewness. Barberis and Huang (2007) also argue that "an investor who overweights the tails of a portfolio return distribution will, of course, value a positively skewed portfolio highly; what is surprising is that he also values a skewed security highly, even if that security is small and independent of other risks". The non-rational weighting of probabilities under uncertainty is explained more extensively in cumulative prospect theory (Kahneman and Tversky, 1992). The theory emphasizes that investors tend to overestimate low probabilities while underestimate medium probabilities.

Figure 2 - Probability weighting in cumulative prospect theory

The figure shows how individuals estimate the likelihood of the realizations of different probabilities in comparison with the actual likelihood. The x-axis exhibits different likelihoods, the y-axis shows the cumulative probabilities. The blue line is the bisecting line, combining the actual probabilities and actual cumulative probabilities. The yellow and blue lines incorporate the estimated likelihood of the real probabilities and connect them to estimated cumulative probabilities. The pink line shows probabilities for gains, while the yellow line represents probabilities for losses.

(Kahneman and Tversky, 1979 and 1992)



Accordingly, Conrad, Dittmar, and Ghysels (2009) also demonstrate that positive skewness and subsequent returns have a negative effect on each other and that skewness of individual stocks does matter. As Barberis and Huang (2007) show these positively skewed stocks can actually deliver negative average excess return. However, as Boyer et al. (2009) argue, this overpricing persists and is not exploited by arbitrageurs. According to Barberis and Huang (2007), the overpricing is not arbitraged away because it entails significant risks and costs. If an investor's strategy would be to short many positively skewed stocks in order to exploit their negative expected excess returns, he would end up with a very negatively skewed portfolio, and it would be very costly and risky to diversify this portfolio. Furthermore, short-selling itself contains additional costs and pitfalls. The strategy might involve short-selling fees, and there is the risk that the stocks used in the transaction are recalled before the strategy would pay off. These can all be reasons why investors do not trade aggressively against these positively skewed assets.

2.5. Noise trading

Besides idiosyncratic skewness, idiosyncratic volatility is another important characteristic that also has a negative relation with the average stock return as it is shown by Stambaugh, Yu, and Yuan (2012). They argue that this effect is even stronger for overpriced stocks that might easily be the case in a lottery stock that has positive idiosyncratic skewness, which, as it has been argued before, many times leads to overpricing. They show that the higher the idiosyncratic volatility of a stock, the greater its arbitrage risk; consequently these stocks are more disposed to be overpriced because short sellers perceive the risks to be higher than the potential gains from a strategy of trading against these stocks. They argue that this risk can partly be explained by noise-trader risk (Shleifer and Vishny, 1997), which means that due to adverse price movements and capital constraints, the short seller has to close his position before the strategy of mispricing correction could earn a profit for him.

Black (1986) used the notion of noise trader for individual investors who have less information and trade based on their own research; therefore, they act irrationally on noise as if it were unique valuable information that is only available for them. They are usually trend followers, over-react to good and bad news, and have a bad timing. The above mentioned noise trader risk for short-seller arbitrageurs is the risk that in the case the price of a stock is already pushed up due to bullish arbitrageurs, they might become even more bullish tomorrow, and push up the price even further before it would return to its more fundamental value which would generate profit for the short-seller. De Long et al. (1990) argue that because the beliefs of noise traders are unpredictable and many times irrational, prices of assets can diverge from their fundamental value even if there is no fundamental risk. This means that noise itself creates additional risk that deters many arbitrageurs. If an arbitrageur, in spite of this additional risk, tries to trade against noise traders, he might trade rather based on predictions about the pseudo signals noise traders follow, than on the fundamentals of the underlying stock. These signals can include volume and price patterns, sentiment indices, or forecasts from investment advisers and popular financial newspapers. De Long et al. (1990) show that noise trading risk can explain several puzzles in the financial world, such as excess volatility of asset prices, mean reversion of stock returns, underpricing of closed-end mutual funds, and the Mehra-Prescott equity premium puzzle. Froot and Dabora (1998) use the noise trader theory as one argument to explain the deviation of twin stock prices from each other. They argue that each stock of the twin co-moves more with market in which it is traded the most, because locally traded stocks are more affected than foreign traded stocks by market specific shocks by noise traders.

Based on these research it can be concluded that the conditions for the mispricing to endure are the risk aversion and the short time horizon of arbitrageurs. Discovering and exploiting mispricing is costly, especially if the noise trader risk is systematic. On the other hand, if arbitrageurs' horizon lengthens, the impact of noise traders can be reduced.

3. Motivation for topic choice

As it can be seen from the previously described literature, several research have already been done in the fields of lottery stocks, noise trading theory, (cumulative) prospect theory, and individual investor's biases. However, it is much more rare to find research that combines several of these topics, and even if they do, most of the time the research is focused only on the U.S.

Therefore, we felt that by combining these fields and investigate lottery stocks in Sweden during the beginning of the financial crisis might give a new, interesting, and relevant perspective on the trading activities of Swedish individual investors in these stocks; on what effect their trades have on the price of these stocks; and on how arbitrageurs can go against these individuals and make money. Since research in the field of lottery stocks in Sweden is not very extensive, the results of our analysis might be a good starting point for further research in this topic in Scandinavia.

3.1. Hypothesis

Individual investors constitute a big portion of investors in the market, and they have disadvantages in knowledge, information, and tools compared to institutional investors. Furthermore, they are much more influenced by behavioural biases, which become even stronger during times of high uncertainty and market decline, like the period we experienced in the last couple of years. This is why individual investors not only can influence the price of stocks but also can create persistent noise trader risk in the market.

From the previous section we could see that several papers have already tried to find a link or causal relationship between the various biases and moods in investors' behaviour. And many of these research found that feelings and emotions play an important part in the investment decisions of individual investors. Furthermore, it has been shown that retail investors are especially prone to gamble and buy lottery stocks. Therefore, we are interested in whether this phenomenon is true for Swedish individual investors as well, and whether they are also attracted to such lottery stock features as low price, idiosyncratic volatility, and idiosyncratic skewness.

As it has been described in prospect theory, during difficult times individual investors might accept gambles that they would otherwise (in normal times) reject. Therefore, we would like to understand better this risk-seeking behaviour in times of stock market decline, and examine whether Swedish individual investors are desperate enough in difficult periods so that they invest a relatively higher volume in lottery type assets.

It is an interesting question, because as we can see from previous papers, mainly those investors buy lottery stocks that are in poverty or in a lower social class than they want to be in. However, lottery stocks most of the time become overvalued; therefore, they underperform non lottery stocks. Consequently, if these individual investors put a bigger portion of their portfolio in this kind of stocks, they will get the opposite result than what they expected and wished for. The noise trading theory might help us to understand better why potential arbitrageurs cannot benefit from lower expected returns of lottery stocks.

To sum up, there are four main hypotheses that we will test:

H1: Individual investors prefer lottery features, such as low price, high idiosyncratic skewness and high idiosyncratic volatility. Individual traders therefore have a relative higher share of the total volume in stocks with low prices, high idiosyncratic skewness and high idiosyncratic volatility.

H2: Individuals are more prone to accept gambles when they are in the domain of losses. They are seeking for stocks with lottery features in times of negative stock market returns because they overweight the low probability of high expected returns of these stocks. Therefore, online traders excessively net buy lottery stocks in times of downward market movement.

H3: Excess net buy of lottery stocks by online traders contributes to overpricing. As a consequence, lottery stocks underperform nonlottery stocks in the mid- and long-term.

H4: Due to noise trading, it is risky for arbitrageurs to trade aggressively against these individual investors who load on lottery stocks; therefore, the mispricing of these assets can persist for a longer time.

4. Data

Since the focus of our research is on Swedish investors, the main data set we use are Swedish equity trading data from the Stockholm Stock Exchange (SSE). SSE is a fully electronic limit order book market with brokers matching the order flow in exchange for fixed and transaction based fees. The obtained daily trading data cover the period between January 02, 2006 and January 30, 2009. For each trading date and stock, our data set shows the number of trades executed and the volume and turnover of stocks traded, measured in Swedish Kronor (SEK), and all the data is split up based on whether the trades were purchases, sales, or internal trading. A crucial advantage of the data set is that it also differentiates between online and non-online trader, which we will use as a proxy for a differentiation between individual and institutional investors.

In order to complement the data set from SSE, we obtained the corresponding stock price data from Datastream. We then matched our existing database with the prices based on the stocks' ISIN code. After that, by using the daily price data we calculated the daily return for each stock in the data set.

Furthermore, we cleaned the data set in such a way that we disregarded stocks for which there was a low number of observations of trade, and also disregarded prices lower than 1 SEK because they are very extreme outlier prices and can distort the results considerably. After the cleaning process, we are left with 343 stocks that will comprise our main data set. Throughout our calculations we proxy for individual investors by the online traders in the data set. This seems a reasonable proxy, since at the broker firms most of the online traders are individuals. Consequently, the non-online traders will constitute the other side of the market, namely the institutional investors.

Besides the brokerage data and the corresponding prices, we needed a proxy for the market as a whole and for the risk-free rate for the calculation of the excess market return. As market return we used the return of the OMXS30 index that is the leading share price index of the Stockholm Stock Exchange. It consists of the 30 most actively traded stocks on the SSE. The data for this market index we obtained from the Nasdaq OMX Nordic website.

As proxy for the risk-free rate we used the 1-year Swedish Treasury-bill, for which we obtained the data from the Riksbank website.

5. Methodology and Results

5.1. Preferences of individual investors

As a first step, in order to analyze whether Swedish individual investors are in general attracted to features that are attributed to lottery stocks, such as low share price, high idiosyncratic skewness, and high idiosyncratic volatility, we calculate these characteristics for each stock in our data set.

For the calculation of idiosyncratic skewness we followed the method described by Kumar (2009) and Harvery and Siddique (2000). The first step in the procedure is to run a regression by fitting a two-factor model on the daily stock returns time series, where the two factors are the excess market returns and the squared excess market returns. As a second step, to obtain the idiosyncratic skewness, the scaled measure of the third moment of the residuals from the previous regression has to be calculated. In this case the daily return time serious refers to the previous 6 months (from t-6 to t-1) of data. Since throughout time stock characteristics might change, this regression is done as a rolling window that goes forward one month at a time. Consequently, we obtain 31 monthly idiosyncratic skewness values for each stock in the data set, ranging from July 2006 until January 2009.

Formula 1 - idiosyncratic skewness and idiosyncratic volatility calculation

Formula 1 shows the basis for the calculations of idiosyncratic skewness and idiosyncratic volatility. Daily returns for each stock are run on the daily excess market return and the daily squared excess market return.

$$r_t^i = \alpha + \beta * r_t^{excess\ market} + \delta * r_t^{excess\ market}{}^2 + \varepsilon_t \quad (1)$$

Formula 2 - idiosyncratic skewness

For the calculation of the idiosyncratic skewness the residuals from Formula 1 are taken and in each months the skewness of the residuals are calculated

$$Idiosyncratic\ Skewness_T^i = \frac{n}{(n-1)(n-2)} \frac{\sum_{t=1}^{n}(\varepsilon_t - \varepsilon)^3}{\sigma^3} \quad (2)$$

Formula 3 - idiosyncratic volatility

For the calculation of the idiosyncratic volatility the residuals from Formula 1 are taken and in each months the standard deviation of the residuals are calculated

$$Idiosyncratic\ Volatility_T^i = \sqrt{\frac{1}{(n-1)} \sum_{t=1}^{n}(\varepsilon_t - \varepsilon)^2} \quad (3)$$

Although in previous papers researchers used several different ways of calculating idiosyncratic volatility, we calculate it with the same method as we use for idiosyncratic skewness since we didn't have access to data of a Fama French model for Sweden. Several researchers, such as Kumar (2009) used a U.S. Fama French model for the skewness calculatios. The only difference is that we calculate the standard deviation of the residuals obtained from equation (1) and not the standard deviation of the residuals that are obtained by running a regression of the returns on a fitted Fama French model. The corresponding time frame is the previous 6 months in this case as well. Due to the monthly rolling window regression, we obtain 31 monthly idiosyncratic volatility values for all stocks in the data set.

The stock price calculation is much simpler; here we use the price at the end of month t-1. In order to match the idiosyncratic skewness and idiosyncratic volatility measures calculated earlier, we create a time series with the 31 monthly prices.

Once we obtained the three lottery type characteristics, we divided the sample based on deciles of these dimensions and calculated the proportion of individual investors in the total trading turnover and in the total number of trades in all the stocks in the data set.

Figure 3 - shares of individual investors in the total turnover

Figure 3 shows the share individual investors have in the total turnover of stocks with different characteristics. The stocks are divided in deciles of prices, idiosyncratic skewness and idiosyncratic volatility and show the share individuals take in the total volume in the different deciles of the three characteristics.

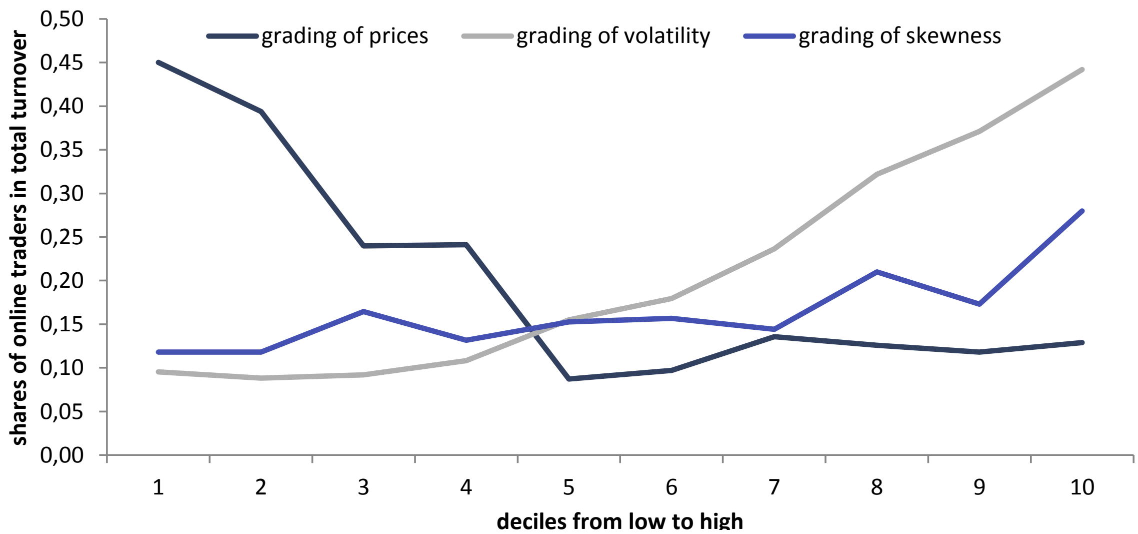
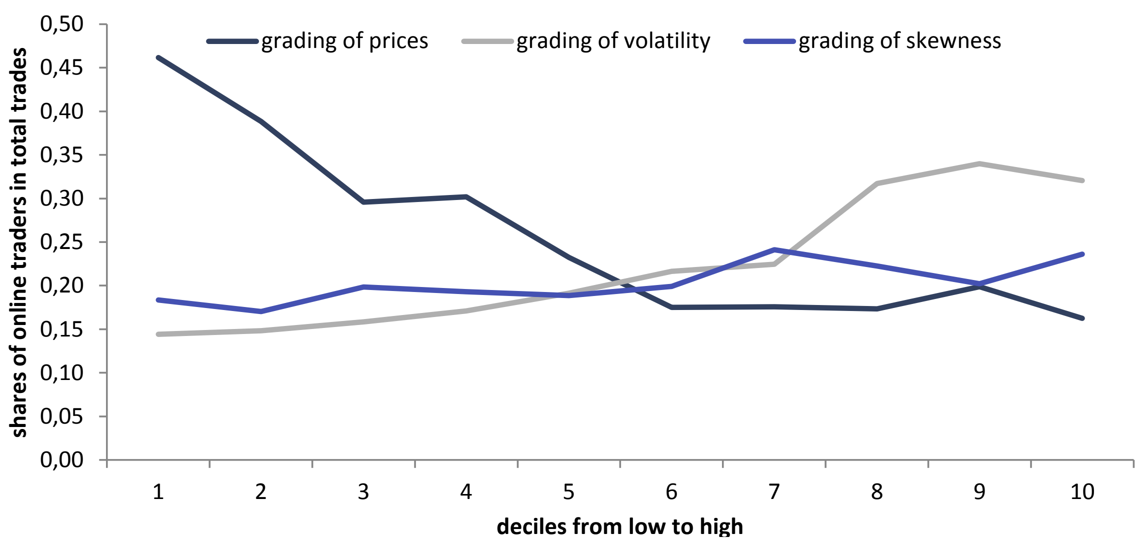


Figure 4 - shares of individual investors in the total number of trades

Figure 4 shows the share individual investors have in the total number of trade of stocks with different characteristics. The stocks are divided in deciles of prices, idiosyncratic skewness and idiosyncratic volatility and show the share individuals have in the total number of trades in the different deciles of the three characteristics.



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As we can see, in our sample individual investors have a larger share in the whole trading volume of stocks with low prices, of stocks with high idiosyncratic skewness and of stocks with high idiosyncratic volatility. There is a clear tendency that the share of individuals in the total trading volumes and in the total number of trades increases when idiosyncratic volatility and idiosyncratic skewness increase or the price decreases. Altogether we see that individual investors are relatively more interested in stocks that have certain features that can be attributed to lotteries and lottery stocks, such as low price, high idiosyncratic volatility, and high idiosyncratic skewness. This also means that individual investors could have a big impact on the prices and returns of stocks that have these lottery features.

Based on the results, we can accept our 1st hypothesis, that Swedish individual investors have a preference for lottery features, such as low price, high idiosyncratic skewness and high idiosyncratic volatility.

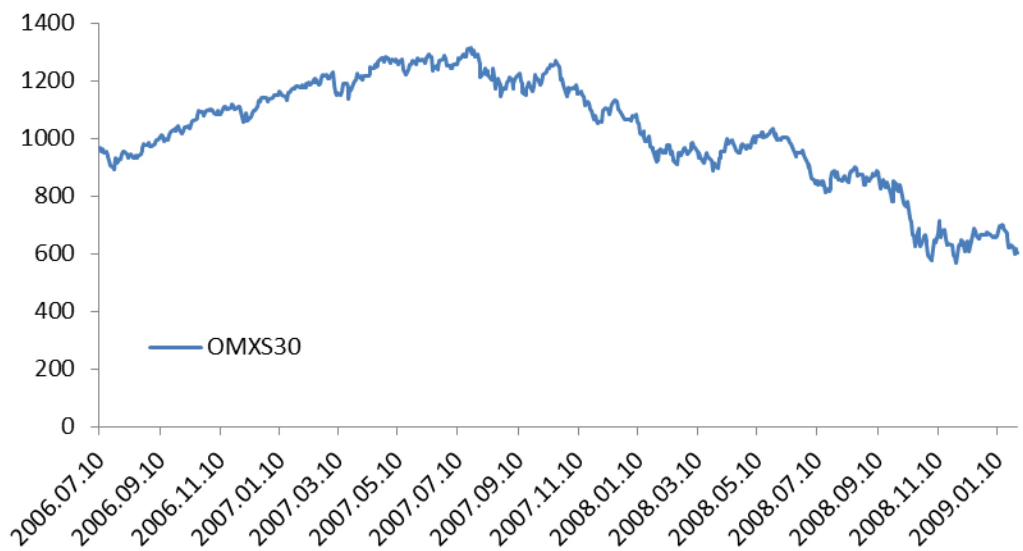
5.2. The lottery portfolio

Now that we established that Swedish individual investors indeed have a preference for lottery features, we are interested in whether they are attracted also to lottery stocks that incorporate all these characteristics at the same time. Especially, we want to investigate whether they excessively net buy these stocks in times of poor market performance, because based on prospect theory, we would expect that individuals become more risk-seeking and their preference for gambling increases when they are in the domain of losses.

The time period of our analysis seems very adequate for this analysis, since it contains the beginning of the last financial crisis; therefore, we can easily observe the effect of a big market decline on individual investors' behavior regarding their trading activities. We use the OMXS30 index as a proxy for the general market movement in Sweden. The performance of the OMXS30 index during the period of our study can be seen in figure 5.

Figure 5 - performance of OMXS30 index

Figure 5 shows the development of the OMXS30, the main stock index in Sweden between July 2006 and January 2010 which is the period that we look at in our paper.



For the selection of lottery stocks we build on the procedure described and used by Kumar (2009). According to this method, based on the monthly lottery stock characteristics, we sort the stocks in our data set based on price, idiosyncratic volatility, and idiosyncratic skewness. Firstly, we choose the stocks that belong to the lowest k^{th} price percentile. Secondly, from these stocks, we select the ones with highest k^{th} idiosyncratic skewness percentile. Finally, among the remaining stocks we select the ones within the highest k^{th} idiosyncratic volatility percentile. As this selection procedure seems to be a bit arbitrary, especially the choice of k, we decided to use different orders of the lottery feature selection and different k-values. We are interested in the potential differences in the results of the various selection procedures. So in total we calculate the lottery portfolio in 18 different ways: with k=50, 40, and 30; and with the six different orders of the three lottery stock characteristics. The following table shows which type corresponds to which order of selection.

Table 1 - Order of selection of lottery stocks

Table 1 includes the different orders for the picking of the lottery stocks.

	Order of selection		
	1.	2.	3.
Type 1	price	idiosyncratic skewness	idiosyncratic volatility
Type 2	price	idiosyncratic volatility	idiosyncratic skewness
Type 3	idiosyncratic skewness	price	idiosyncratic volatility
Type 4	idiosyncratic skewness	idiosyncratic volatility	price
Type 5	idiosyncratic volatility	price	idiosyncratic skewness
Type 6	idiosyncratic volatility	idiosyncratic skewness	price

After deciding about the lotterystock selection procedure, we calculated the 18 different sets of lottery stocks. Furthermore, since we recalculated on a monthly basis the lottery stock characteristics, we also rebalanced these lottery “portfolios” based on the time-varying characteristics of the stocks. In the following table a short comparison can be seen about lottery and nonlottery stocks summed up in the three different cut-off rates (k).

Table 2 – Basic characteristics of lottery and non-lottery stocks

Table 2 compares the characteristics that serve as lottery calculations for lottery stocks and non-lottery stocks

	k=50		k=40		k=30	
	Lottery-Type	Non-lottery-Type	Lottery-Type	Non-lottery-Type	Lottery-Type	Non-lottery-Type
Number of stocks	39	304	30	313	20	323
Price	12,29	125,00	14,66	121,34	17,12	117,36
Idiosyncratic Skewness	1,5468	0,2555	1,8576	0,2614	2,3135	0,2880
Idiosyncratic Volatility	0,0506	0,0256	0,0536	0,0260	0,0582	0,0267

By definition the stocks within the lottery portfolio have lower prices and higher idiosyncratic skewness and higher idiosyncratic volatility. In the appendix further tables are shown about the characteristics of other types of lottery calculation and the transition matrix of lottery stocks. The transition matrix shows which portion of the lottery portfolio changes from one month to the next. It can be seen from the tables that approximately 8-30% of the stocks are changing month-by-month in the lottery portfolio. It can also be observed that within 6-10 months half of the stocks in the lottery portfolio are replaced by other stocks.

5.3. Relation between lottery net buy imbalance and market return

Now that we have created the lottery portfolios, we can analyze the relation between the daily market movements and individual investors' daily net buy imbalance of lottery stocks. The imbalance shows the relative excess demand of individual investors in lottery stocks over the general relative demand of individual investors in all stocks and is defined by the difference between the net buy ratio of individual investors in the lottery portfolio and the net buy ratio of individual investors in the whole data set:

Formula 4 - net buy imbalance

The net buy imbalance is used for our further imbalance calculation and is calculated as the difference of the net buy ratios of individual investors in lottery stocks and of the net buy ratios of individual investors in the stocks of our whole sample

$$Imbalance_t = \frac{Askvolume_t^{lottery} - Bidvolume_t^{lottery}}{Askvolume_t^{lottery} + Bidvolume_t^{lottery}} - \frac{Askvolume_t^{total} - Bidvolume_t^{total}}{Askvolume_t^{total} + Bidvolume_t^{total}} \quad (4)$$

In order to observe the relationship between the market movement and individuals' buying activities in lottery stocks, we calculate the correlation between the two time-series, the lottery net buy imbalance by individual investors and the performance of the OMXS30 index. The results are shown in the following table:

Table 3 - correlation net buy imbalance and OMXS30 returns

Table 3 shows the correlation between the net buy imbalance of individual investors for the different type of lottery portfolios and the return of the OMXS30

k	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
30	-0,22	-0,20	-0,20	-0,19	-0,18	-0,17
40	-0,21	-0,20	-0,20	-0,18	-0,19	-0,18
50	-0,14	-0,20	-0,17	-0,15	-0,18	-0,17

As it can be seen from the results, in all cases the correlation between the two series is negative. Although this negative relation does not necessarily mean causal relationship between the factors, the calculations clearly show that in times when the market performance is poor, individuals excessively net buy lottery stocks. Another support for this is the evidence that for the whole sample, including the non-lottery stocks, individual investors' net buy ratios are positively correlated with the market return (0,3202), which means that individuals are not in general net buying stocks when the market return is negative.

This confirms our 2nd hypothesis, although we have to be cautious regarding the issue of causality. Prospect theory which states that when individuals are in the domain of losses (that can easily be a case in times of poor market performance) they are more risk-seeking and are willing to gamble more can help to explain these results. Individual investors are more attracted to riskier stocks with high idiosyncratic volatility when the market return is negative. Additionally, they are more appealed to potential high returns in order to gain back former wealth and invest in stocks with a high positive skewness which can explain the excess net buy of lottery stocks by individuals in these times.

5.4. Effect of individual's net buy imbalance on lottery portfolio performance

Now that we have observed that when the market is going down, individuals excessively net buy lottery stocks, we want to analyze what effect an increased preference for lottery stocks has on the prices of these stocks. To observe this effect we run a regression of the return of the market index on individuals' preference for lottery stocks. It is built up as a rolling regression and tries to explain the monthly returns of the lottery portfolio going forward by the monthly net buy imbalance of individuals at a fixed given point in time.

The rolling regression starts at day t = 0 and looks at the price driving effect of the individual investors' trading in the lottery stocks. The rolling window is on a monthly basis, and as the time range of the lottery returns increases the coefficient of the imbalance will show us whether the price driving effect will hold in the future or whether the price driving at t = 0 will be reversed in the future.

Formula 5 - regression of lottery returns on market return and lottery net buy imbalance of individual investors

The regression is used to observe what impact a positive lottery net buy imbalance of individual investors at a certain point in time has on the subsequent returns of these lottery stocks. The dependent variable is the return of the lottery portfolio. The independent variables are the return of the OMXS30 and the net buy imbalance of individual investors in the lottery portfolio. For the first observation we use daily observations at day t=0. In the rolling regression we start with a one month observation. Every time one month is added for the returns in order to see the long-time effects of the imbalance at a certain point of time.

$$r_{0:t}^{lottery_{t=0}} = \alpha + \beta * r_{0:t}^{market} + \delta * Imbalance_{t=0} + \varepsilon \quad (5)$$

Table 4 - regression results for k=50[3]

Table 4 shows the results of Regression 5. Given are the coefficients and the t-statistics in parenthesis. Coefficients with statistical significance (p-values) are marked with stars.

[3] *=significance level10%, **=significance level 5%, ***=significance level1%

t	Type 1				Type 2			
	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0009 (-0,0856)	0,5089*** (0,0000)	0,0110* (0,0087)	0,3255	-0,0008 (0,0917)	0,5005*** (0,0000)	0,0111** (0,0082)	0,3528
1	-0,0135 (-1,3521)	0,7814*** (3,7722)	-0,0696 (-1,8946)	0,3719	-0,0134 (-1,3818)	0,7775*** (3,8650)	-0,0903 (-2,6387)	0,4223
2	-0,0131 (-0,9223)	1,1079*** (6,1263)	-0,0969 (-1,8825)	0,6088	-0,0185 (-1,3564)	1,0778*** (6,1921)	-0,1195 (-2,5126)	0,6330
3	0,0051 (0,2891)	1,2205*** (7,5332)	-0,0296 (-0,4650)	0,7004	-0,0043 (-0,2606)	1,1318*** (7,4100)	-0,0833 (-1,4472)	0,7170
4	0,0235 (1,3259)	1,2728*** (9,9663)	-0,0214 (-0,3422)	0,7979	0,0074** (0,4565)	1,1856*** (10,1310)	-0,0804 (-1,4647)	0,8123
5	0,0338** (1,5236)	1,3026*** (9,8027)	-0,0524 (-0,6791)	0,7905	0,0083*** (0,4541)	1,2657*** (11,6376)	-0,1269 (-2,0926)	0,8471
6	0,0488*** (2,0868)	1,3228*** (11,0926)	0,0252 (0,3142)	0,8291	0,0203*** (0,8648)	1,2400*** (10,3955)	-0,0537* (-0,6975)	0,8138
7	0,0615*** (2,4583)	1,3313*** (11,7715)	0,0675 (0,7537)	0,8506	0,0311*** (1,2481)	1,2581*** (11,2623)	-0,0061 (-0,0701)	0,8395
8	0,0723*** (3,4523)	1,3532*** (15,7568)	0,0451 (0,6179)	0,9146	0,0411*** (2,0082)	1,2628*** (15,2315)	0,0041* (0,0593)	0,9093
9	0,0651*** (3,6148)	1,3161*** (18,8045)	-0,0833 (-1,2618)	0,9435	0,0315*** (1,8131)	1,2056*** (18,0284)	-0,0960 (-1,5259)	0,9400
10	0,0737*** (3,5375)	1,3270*** (17,2614)	-0,0919 (-1,2416)	0,9362	0,0339*** (1,4428)	1,2183*** (14,2026)	-0,1062* (-1,2890)	0,9098
11	0,0733*** (3,4096)	1,3273*** (17,6200)	-0,1021 (-1,2889)	0,9392	0,0320*** (1,4165)	1,2157*** (15,6376)	-0,0993 (-1,2102)	0,9241
12	0,0771*** (3,9524)	1,2841*** (19,3083)	-0,0856 (-1,2122)	0,9515	0,0363*** (1,9822)	1,2184*** (19,9361)	-0,1253 (-1,9148)	0,9542
13	0,0799*** (4,0440)	1,2721*** (19,5115)	-0,0531 (-0,7440)	0,9558	0,0547*** (2,7635)	1,2047*** (18,8690)	-0,0715 (-1,0114)	0,9524

	Type 3				Type 4			
t	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0009 (0,0856)	0,5081*** (0,0000)	0,0104** (0,0085)	0,3460	-0,0005 (0,2560)	0,4775*** (0,0000)	0,0122** (0,0028)	0,3400
1	-0,0122 (-1,4728)	0,9333*** (5,4695)	-0,0371 (-1,2073)	0,5328	-0,0046 (-0,5654)	0,9290*** (5,5377)	-0,0387 (-1,3350)	0,5413
2	-0,0082 (-0,8023)	1,0968*** (8,4722)	-0,0450 (-1,2013)	0,7404	-0,0021 (-0,1670)	0,9802*** (6,1357)	-0,0719 (-1,6239)	0,6094
3	0,0005 (0,0410)	1,1124*** (9,1111)	-0,0315 (-0,6459)	0,7762	0,0022 (0,1606)	1,0115*** (7,9387)	-0,0926 (-1,8992)	0,7528
4	0,0091 (0,6652)	1,1888*** (12,0835)	-0,0458 (-0,9375)	0,8555	0,0127 (1,1178)	1,2017*** (14,7318)	-0,1212 (-3,1244)	0,9062
5	0,0218* (1,0979)	1,2537*** (10,5797)	-0,0784 (-1,1214)	0,8160	0,0180* (1,4134)	1,2618*** (16,5681)	-0,1810 (-4,2015)	0,9217
6	0,0316** (1,7202)	1,2986*** (13,9058)	-0,0431 (-0,6752)	0,8860	0,0272** (1,5469)	1,2409*** (13,8941)	-0,1395 (-2,3846)	0,8924
7	0,0403*** (2,0511)	1,3470*** (15,2522)	0,0047 (0,0651)	0,9058	0,0368** (1,7620)	1,2641*** (13,5530)	-0,1028 (-1,3832)	0,8863
8	0,0469*** (2,3226)	1,3378*** (16,2574)	-0,0222 (-0,3087)	0,9195	0,0566*** (2,3458)	1,3247*** (13,5873)	-0,1108 (-1,3221)	0,8905
9	0,0461*** (2,2617)	1,3370*** (17,0267)	-0,0877 (-1,1490)	0,9318	0,0693*** (2,7704)	1,3418*** (13,9959)	-0,1702 (-1,8514)	0,9067
10	0,0496*** (2,5038)	1,3273*** (18,3337)	-0,0958 (-1,3328)	0,9428	0,0787*** (2,7694)	1,3730*** (13,2964)	-0,1702 (-1,6819)	0,9004
11	0,0492*** (2,3015)	1,3364*** (17,8961)	-0,1345 (-1,7181)	0,9411	0,0717*** (2,5434)	1,3991*** (14,4164)	-0,2354 (-2,3203)	0,9137
12	0,0558*** (2,2401)	1,2805*** (15,1421)	-0,1086 (-1,2139)	0,9230	0,0737*** (3,1028)	1,3827*** (17,4717)	-0,2116 (-2,5270)	0,9412
13	0,0610*** (2,4192)	1,3246*** (15,9898)	-0,1278 (-1,4106)	0,9345	0,1067*** (3,9300)	1,4284*** (16,4234)	-0,1356 (-1,4222)	0,9373

	Type 5				Type 6			
t	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0005	0,5097***	0,0106***	0,3870	-0,0004	0,5279***	0,0085**	0,4063
	(0,2389)	(0,0000)	(0,0103)		(0,4447)	(0,0000)	(0,0357)	
1	-0,0010	0,9758***	-0,0495	0,6140	0,0031	0,9897***	-0,0211	0,5804
	(-0,1337)	(6,3305)	(-1,9141)		(0,3920)	(6,0383)	(-0,7687)	
2	0,0016	0,9198***	-0,0760	0,6374	0,0098	1,0158***	-0,0366	0,6291
	(0,1420)	(6,4793)	(-1,9879)		(0,8125)	(6,5839)	(-0,8802)	
3	0,0076	0,9131***	-0,1012	0,7604	0,0161	1,0493***	-0,0606	0,7449
	(0,6125)	(7,9882)	(-2,3845)		(1,1437)	(8,0346)	(-1,2478)	
4	0,0139	1,1084***	-0,1166**	0,8809	0,0232	1,2090***	-0,0959**	0,8874
	(1,1732)	(12,9441)	(-2,9485)		(1,8780)	(13,5049)	(-2,3189)	
5	0,0215**	1,2442***	-0,1405*	0,9194	0,0340**	1,3213***	-0,1433	0,9234
	(1,7280)	(16,6016)	(-3,4129)		(2,6318)	(17,0129)	(-3,3574)	
6	0,0291***	1,2561***	-0,0803**	0,8979	0,0457***	1,3155***	-0,0784	0,8965
	(1,7370)	(14,6325)	(-1,4704)		(2,5735)	(14,4696)	(-1,3549)	
7	0,0339***	1,2817***	-0,0618**	0,9002	0,0627***	1,3549***	-0,0374	0,9037
	(1,7596)	(14,6831)	(-0,9251)		(3,1387)	(14,9847)	(-0,5406)	
8	0,0480***	1,3291***	-0,0702	0,9082	0,0789***	1,3964***	-0,0682	0,9265
	(2,2329)	(15,0707)	(-0,9664)		(3,9256)	(16,9576)	(-1,0039)	
9	0,0463***	1,3058***	-0,1460	0,9246	0,0799***	1,3607***	-0,1788	0,9574
	(2,1956)	(15,9092)	(-1,9332)		(4,8466)	(21,2090)	(-3,0504)	
10	0,0461***	1,3115***	-0,1534	0,9199	0,0817***	1,3542***	-0,1533	0,9516
	(1,9592)	(15,0978)	(-1,8787)		(4,3648)	(19,5812)	(-2,3750)	
11	0,0394***	1,3287***	-0,2060	0,9240	0,0725***	1,3616***	-0,1926	0,9485
	(1,6178)	(15,5614)	(-2,3466)		(3,5416)	(19,0870)	(-2,6457)	
12	0,0539***	1,3553***	-0,1923	0,9448	0,0740***	1,3863***	-0,1859	0,9300
	(2,4540)	(18,0811)	(-2,4720)		(2,8814)	(15,9491)	(-2,0768)	
13	0,0840***	1,3738***	-0,1038	0,9310	0,1097***	1,4261***	-0,0817	0,9308
	(3,1288)	(15,5214)	(-1,0999)		(3,8928)	(15,5366)	(-0,8406)	

The returns of the lottery portfolio are positively correlated with the market return. The beta coefficients are positive for all types of lottery stock calculations and are significant for every time horizon. The concurrent delta coefficients that measure the impact of the imbalance on the lottery return on the same day are positive and significant at least at the 5% significance level (except type 3, k=30). For later time horizons in most of the cases the deltas have a negative sign and are especially significant for types 4, 5 and 6. The positive and significant net buy imbalance of individual investors in lottery stocks at time t = 0 increases the price and the return of the lottery portfolio. Also for the following months values of alpha in most cases are negative, however only rarely statistically significant.

This shows that individual investors can drive the price of lottery stocks and have an upward price pressure on these stocks in the short-term. In the longer run a reverse effect can be seen. This can be explained by the fact that due to the upward price pressure by individual investors, the prices of lottery stocks overshot in the short run, and therefore, have lower returns in future periods. However, for the long-term effect we have to be a little bit more careful with our interpretation as the coefficients are not always statistically significant and even can change the sign.

For the results of k=40 and k=30, please see Table 8 and Table 9 in the appendix.

5.5. Effect of individuals' net buy ratio on the return of the whole data set

In order to investigate whether the findings of the previous section are unique for lottery stocks or whether this relationship holds in general, we performed a similar analysis for the whole data set. As on the level of the whole sample an imbalance ratio cannot be calculated we ran a rolling regression of the sample return on the market return and on the individuals' net buy ratio of the stocks in the whole sample. Just as in the previous section, the rolling window of the two returns serious is on a monthly basis, while the net buy ratio is fixed at a given point in time.

Formula 6 - regression of individual returns on market return and individual net buy ratio

Formula 6 is used to look at what impact the net buying activities of individual investors at a certain point in time (day t=0) have on the subsequent returns of the sample. The dependent variable is the return of the sample. The independent variables are the OMXS30 return and the net buy ratio of individual investors at a certain point in time. As this is a rolling regression one month is added at the market return and the return of the whole sample after each run in order to see the long-time effects of the net buy ratio.

$$r_{0:t}^{sample} = \alpha + \beta * r_{0:t}^{market} + \delta * Netbuyratio_{t=0}^{sample} + \varepsilon \qquad (6)$$

Table 5 - regression results[4]

Table 5 shows the results of formula 6. It shows the impact of the OMXS30 return on the return of the stocks in the whole sample as well as the impact of the imbalance of individual investors at a certain point of time on current and future returns of the whole sample. Statistically significant coefficients (p-values) are marked with stars. T-statistics are below the coefficients within brackets.

[4] *=significance level10%, **=significance level 5%, ***=significance level1%

t	alpha	market return	online imbalance	adj. Rsquared
0	-0,0004 (-1,1979)	0,6710*** (36,1831)	-0,0045 (-0,7613)	0,6893
1	-0,0026 (-0,3828)	0,7931*** (5,5324)	0,0284 (1,1391)	0,5370
2	-0,0037 (-0,3481)	0,8764*** (6,4335)	0,0209 (0,5493)	0,6136
3	-0,0006 (-0,0480)	1,0698*** (9,8525)	0,0017 (0,0413)	0,8009
4	0,0017 (0,1543)	1,1663*** (14,6972)	0,0089 (0,2326)	0,8974
5	-0,0004 (-0,0337)	1,1642*** (14,7344)	0,0327 (0,7246)	0,8964
6	0,0006 (0,0462)	1,1434*** (16,7159)	-0,0018 (-0,0392)	0,9182
7	0,0029 (0,2355)	1,1291*** (20,3143)	-0,0231 (-0,5185)	0,9449
8	0,0023 (0,1933)	1,1011*** (22,8176)	0,0102 (0,2442)	0,9577
9	-0,0049 (-0,3967)	1,0634*** (22,4025)	0,0762 (1,6439)	0,9603
10	-0,0063 (-0,5473)	1,0592*** (25,1681)	0,0881** (2,0973)	0,9697
11	-0,0014 (-0,1397)	1,0970*** (30,5349)	0,0859** (2,2231)	0,9791
12	0,0045 (0,3484)	1,0984*** (25,1716)	0,0410 (0,8615)	0,9709

Similar to the regression performed for the lottery portfolio the beta coefficients that measure the impact of the market return are positive and significant. The delta coefficients, however, show a different pattern. At day t = 0 delta has a negative sign and is not significant. In the long run the coefficients are mostly positive and not significant either. We can therefore conclude that individual investors fail to influence the sample return and a positive net buy ratio does not have a price driving effect neither in the short run, nor in the long run. Therefore, the phenomena that individuals influence prices can be narrowed down to lottery stocks only, in our sample.

5.6. Lottery portfolio performance

So far we have shown that individual investors can affect the prices and returns of lottery stocks. Individual investors with a positive net buy imbalance in lottery stocks drive up the prices in the short run; however, this creates overpricing and results in lower expected returns. Now we are interested in how strong this overpricing is and in the underperformance of the lottery stocks compared to all other stocks in the mid-, and long-term after day t=0. Due to the limits of our data set, we will only perform this analysis for returns up to 12 months in the future.

For the analysis we ran a rolling regression on a monthly basis of lottery returns on returns of non-lottery stocks.

Formula 7 - regression of lottery returns on non-lottery returns

Formula 7 has the returns of lottery portfolios as dependent variable and the returns of non-lottery stocks as independent variable. As this is a rolling regression one month is added at both sides after each run in order to see the long-time performance of the two portfolios compared to each other.

$$r_{0:t}^{lottery} = \alpha + \beta * r_{0:t}^{non-lottery} + \varepsilon \qquad (7)$$

Table 6- regression results for k=50[5]

Table 6 shows the results of Formula 7. It shows the relationship between non lottery and lottery stocks for different time horizons. Alpha coefficients show the over/under performance of the lottery portfolio in relation to the performance of the non-lottery stocks. Statistically significant coefficients (p-values) are marked with stars. T-statistics are below the coefficients within brackets.

[5] *=significance level10%, **=significance level 5%, ***=significance level1%

	Type 1			Type 2			Type 3		
t	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared
1	0,0016	0,8155***	0,6354	0,0018	0,7842***	0,6151	-0,0029*	0,8168***	0,6193
	(0,2159)	(7,2992)		(0,2366)	(6,9964)		(-0,3707)	(7,0564)	
2	0,0075	1,2910***	0,5473	0,0025	1,2230***	0,5309	0,0001	1,2963***	0,5258
	(0,6102)	(0,0000)		(0,8610)	(0,0000)		(0,9944)	(0,0000)	
3	0,0088	1,3760***	0,3666	0,0035	1,3275***	0,3885	-0,0053	1,4214***	0,3762
	(0,7028)	(0,0003)		(0,8708)	(0,0002)		(0,8218)	(0,0002)	
4	0,0082	1,5311***	0,3028	-0,0012	1,4353***	0,3127	-0,0122	1,6815***	0,3371
	(0,7718)	(0,0014)		(0,9624)	(0,0012)		(0,6739)	(0,0007)	
5	0,0077	1,7599*	0,2025	-0,0108	1,6031**	0,1908	-0,0100	2,1131***	0,2607
	(0,8245)	(0,0107)		(0,7436)	(0,0131)		(0,7822)	(0,0038)	
6	0,0044	1,6273**	0,0930	-0,0134	1,4846*	0,0861	-0,0160	2,2461**	0,1912
	(0,9171)	(0,0713)		(0,7397)	(0,0795)		(0,7039)	(0,0147)	
7	-0,0013	1,3160	0,0323	-0,0183	1,2130	0,0324	-0,0236	1,9634*	0,1149
	(0,9797)	(0,1928)		(0,6895)	(0,1922)		(0,6284)	(0,0542)	
8	-0,0099	1,0865	-0,0010	-0,0266	0,8820	-0,0095	-0,0291	1,6071	0,0510
	(0,8586)	(0,3339)		(0,6008)	(0,3858)		(0,5926)	(0,1490)	
9	-0,0146	0,5616	-0,0372	-0,0305	0,4287	-0,0398	-0,0340	1,0914	-0,0090
	(0,8106)	(0,6502)		(0,5752)	(0,6958)		(0,5742)	(0,3798)	
10	-0,0171	1,5916	0,0259	-0,0346	1,2930	0,0128	-0,0404	1,8872	0,0619
	(0,7858)	(0,2262)		(0,5464)	(0,2729)		(0,5057)	(0,1381)	
11	-0,0301	2,0868	0,0873	-0,0495	1,7031	0,0650	-0,0536	2,3058*	0,1198
	(0,6233)	(0,1042)		(0,3764)	(0,1386)		(0,3751)	(0,0688)	
12	-0,0462	2,3951**	0,1557	-0,0644	1,9757*	0,1186	-0,0682	2,5051**	0,1710
	(0,4243)	(0,0479)		(0,2379)	(0,0756)		(0,2446)	(0,0397)	

	Type 4			Type 5			Type 6		
t	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared
1	-0,0004	0,8254***	0,5811	0,0032	0,8663***	0,5714	0,0049*	0,8909***	0,6045
	(-0,0454)	(6,5278)		(0,3569)	(6,4026)		(0,5657)	(6,8450)	
2	-0,0018	1,2600***	0,5053	0,0042	1,3567***	0,6184	0,0068	1,3780***	0,5789
	(0,9070)	(0,0000)		(0,7569)	(0,0000)		(0,6481)	(0,0000)	
3	-0,0093	1,3267***	0,3438	0,0019	1,4127***	0,4483	0,0014	1,4352***	0,3905
	(0,6914)	(0,0005)		(0,9266)	(0,0000)		(0,9526)	(0,0002)	
4	-0,0170	1,5872***	0,2840	-0,0062	1,6479***	0,3716	-0,0083	1,6709***	0,3173
	(0,5825)	(0,0021)		(0,8147)	(0,0003)		(0,7820)	(0,0011)	
5	-0,0249	1,8440**	0,1892	-0,0137	1,9685**	0,2583	-0,0137	1,9742***	0,2102
	(0,5156)	(0,0135)		(0,6880)	(0,0040)		(0,7228)	(0,0094)	
6	-0,0301	1,9896**	0,1330	-0,0199	2,1988*	0,1990	-0,0215	2,1429**	0,1456
	(0,5041)	(0,0378)		(0,6230)	(0,0129)		(0,6423)	(0,0309)	
7	-0,0328	1,7724*	0,0810	-0,0233	1,9130	0,1215	-0,0204	1,8613*	0,0791
	(0,5197)	(0,0908)		(0,6160)	(0,0490)		(0,7032)	(0,0935)	
8	-0,0310	1,5407	0,0298	-0,0235	1,7985	0,0789	-0,0178	1,7258	0,0442
	(0,6053)	(0,2050)		(0,6552)	(0,0989)		(0,7697)	(0,1650)	
9	-0,0273	1,3519	-0,0015	-0,0220	1,3531	0,0141	-0,0122	1,2061	-0,0092
	(0,6892)	(0,3364)		(0,7068)	(0,2645)		(0,8552)	(0,3813)	
10	-0,0273	2,2690	0,0667	-0,0264	2,1129	0,0912	-0,0158	2,0458	0,0589
	(0,7015)	(0,1295)		(0,6571)	(0,0932)		(0,8130)	(0,1438)	
11	-0,0407	2,6521*	0,1101	-0,0374	2,5180	0,1595	-0,0255	2,4895*	0,1234
	(0,5710)	(0,0779)		(0,5190)	(0,0412)		(0,6911)	(0,0657)	
12	-0,0578	2,8101**	0,1528	-0,0502	2,7101*	0,1929	-0,0416	2,7137**	0,1632
	(0,4015)	(0,0497)		(0,3976)	(0,0301)		(0,5175)	(0,0437)	

For each type of lottery portfolio the beta is bigger than 1 for time horizons t > 2, indicating that the lottery portfolio has a higher risk than non-lottery stocks have. The alpha is positive in the first few months and then turns negative in the long run. This proves our findings in the previous sections that initially the price pressure of individual investors has a positive effect on the performance of lottery stocks; however, in the long run this effect turns negative. Consequently, individuals who invest in these lottery stocks for a longer-term when there is initially a big upward price pressure on these stocks, are worse off than if they would invest in non-lottery stocks.

For the results of k=40 and k=30, please see Table 13 and Table 14 in the appendix.

These findings prove our 3rd hypothesis. However, it has to be noted that the alphas in this last regression are not statistically significant; therefore, even though our findings are economically significant, its explanatory power is weak, so our conclusions have to be interpreted with caution.

5.7. Noise trading risk and arbitrage

So far we have shown that individuals can drive up the prices of lottery stocks in the short run and this can cause overpricing and lower expected returns in the long run. In this last section we want to investigate why can this overpricing emerge and whether there is any trading strategy that can be used to exploit the mispricing.

Rational investors could use this information and implement an arbitrage trading strategy by taking short position in the lottery portfolio and going long in the non-lottery stocks in order to benefit from the low expected returns in the lottery stocks. However, as we have seen in Table 6 the underperformance of lottery stocks cannot be proven with statistical significance. It is likely that arbitrageurs do not take benefit from the expected underperformance of lottery stocks because noise trader risk makes this potentially very costly and risky strategy. Firstly, by implementing this simple long-short strategy an arbitrageur would have a very negatively skewed portfolio that would be costly to hedge. Secondly, short sellers would bear the risk that in the short run the mispricing can become even bigger before the price converges to its fundamental value. Therefore, due to the noise created by individual traders whose trading behavior is influenced by biases and their own beliefs, arbitrageurs with a short horizon might be forced to close the deal before the mispricing becomes smaller and moves in beneficial direction for the short seller.

As we could see in our analysis, this can easily be the case with these lottery stocks. After the upward pressure in the stock price caused by the trades of individual noise traders, the lottery portfolio still outperforms non-lottery stocks in the first few months. However, it is difficult to forecast or anticipate when this trend will turn around and how big the reversal effect is, as many of our results in the last regression are not statistically significant. There is the risk for arbitrageurs that in the next day or next month noise traders will still be bullish and push up the price even more before it could reverse back to its fundamental value. Due to this risk, arbitrageurs might shy away from trading aggressively against lottery stockholders that explains why the mispricing can occur.

Consequently, we have to accept our last hypothesis as well, and conclude that a trading strategy for exploiting the mispricing in lottery stocks involves significant cost and noise trader risk.

6. Conclusion

Our paper investigates the role and effect individual investors have in the trading activities of lottery stocks. In line with findings from previous research which showed that individuals are irrationally tilted towards assets with lottery features such as low price, high idiosyncratic volatility and high idiosyncratic skewness, we find that individual investors trade relatively more in stocks that incorporate these lottery characteristics. According to our state of knowledge this paper is the first that proved this for a Scandinavian country. We are also able to show that the results of research for the U.S. that individuals are net buyers of lottery stocks when the market return is negative hold for Sweden as well. The main result of our paper is that individual investors are noise traders in lottery stocks. In the short-run they drive up prices for lottery stocks, leading to lower expected returns of these stocks in the future. This leaves other investors with a (risky) arbitrage opportunity which however, cannot be exploited in the short-term, likely due to continued noise trader risk and the lottery specific features of the lottery stocks such as the high idiosyncratic volatility which make it too risky to set up an arbitrage strategy to benefit from a long-term price reversal effect.

Our paper is unique in the sense that it exerts several investigations about lottery stocks in Sweden that have so far been done mainly in the U.S. and we show very similar results. Also it uses quite recent data that includes the beginning of the last financial crisis. This period hasn't been covered so far in the research about lottery stocks. Additionally, it is one of the first papers that try to combine aspects of prospect theory and cumulative prospect theory with noise trading theory. It is able to show that noise is created by individual investors whose decisions are led by behavioural biases and their preferences towards certain stock features.

Beyond the scope of our paper are causal relationships between individuals' sentiments and their behaviour. This is in general one of the most difficult tasks in the field of behavioural finance due to the lack of individual data and difficulties to find measurements for sentiments. Left to further research is a portfolio-based analysis of individual investors. For this analysis data for individual investors' portfolio composition is needed with which each investors' exposure towards lottery stocks can be measured. Another more accurate analysis could be done by comparing the price effect of individual investors on lottery stocks in relation to their fundamental values.

Our paper addresses only one potential strategy to benefit from the overpricing of lottery stocks. This can be a basis for further research that uses other trading strategies and longer time horizons. The main criticism of our paper is that due to our data set we are only able to investigate a period of 31 months and only 343 stocks. Especially, for the investigations that are done to uncover a long-term relationship between a positive net buying of individuals in lottery stocks and the return of the lottery portfolio, numbers of observations are very low.

Probably, also due to these shortcomings, some of our results are not statistically significant and have low explanatory power. Therefore, further research in this field should include a data set with a longer time series, and preferably a bigger universe of stocks as well.

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Appendix

Table 7: Lottery stock and non-lottery stock characteristics

This summary table shows the basic characteristics of lottery stocks and non-lottery stocks in our data set. The types describe the different order of selection for the lottery stocks based on the three lottery stocks characteristics, low price, high idiosyncratic skewness and high idiosyncratic volatility. The cut-off percentile for these selections is 50% (k=50) in the base case, then we change this percentile to 40% (k=40) and 30% (k=30).

Type 1	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	15,07	124,61	17,28	121,04	18,87	117,25
Idiosyncratic Skewness	1,6024	0,2477	1,8601	0,2615	2,1868	0,2963
Idiosyncratic Volatility	0,0532	0,0252	0,0573	0,0256	0,0641	0,0263

Type 2	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	16,58	124,39	20,21	120,73	24,61	116,87
Idiosyncratic Skewness	1,7638	0,2249	2,1321	0,2326	2,6443	0,2657
Idiosyncratic Volatility	0,0494	0,0257	0,0517	0,0262	0,0550	0,0269

Type 3	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	12,99	124,90	15,04	121,27	16,46	117,39
Idiosyncratic Skewness	1,4881	0,2638	1,7563	0,2727	2,1420	0,2997
Idiosyncratic Volatility	0,0542	0,0251	0,0580	0,0256	0,0637	0,0263

Type 4	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	8,43	125,55	9,60	121,93	10,95	117,76
Idiosyncratic Skewness	1,3665	0,2808	1,5974	0,2885	1,9505	0,3125
Idiosyncratic Volatility	0,0509	0,0255	0,0548	0,0259	0,0608	0,0265

Type 5	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	11,05	125,17	12,92	121,50	15,55	117,47
Idiosyncratic Skewness	1,5672	0,2526	1,9144	0,2557	2,4730	0,2771
Idiosyncratic Volatility	0,0476	0,0260	0,0497	0,0264	0,0526	0,0271

Type 6	k = 50		k = 40		k = 30	
	Lottery	**Non-lottery**	**Lottery**	**Non-lottery**	**Lottery**	**Non-lottery**
Number of Stocks	39	304	30	313	20	323
Price	9,65	125,38	12,92	121,58	16,29	117,40
Idiosyncratic Skewness	1,4927	0,2630	1,8856	0,2577	2,4843	0,2769
Idiosyncratic Volatility	0,0483	0,0259	0,0501	0,0264	0,0527	0,0271

Table 8 - Transition matrix for Type 1, k = 50
The transition matrix represents the change in the lottery stock portfolio. This matrix has been created for all the six types and for the three cut-off rates. Here we present the first type with the cut-off rate 50. The results for other types with the same cut-off rate are very similar. The table shows that in each month what percentage of the lottery stocks have been part of the lottery stock portfolio in the previous month as

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**
1	1,00	0,77	0,71	0,69	0,69	0,62	0,51	0,54	0,51	0,50	0,47	0,46	0,46	0,44	0,44	0,44	0,35	0,34	0,39	0,39	0,34	0,30	0,29	0,28	0,23	0,23	0,20	0,30	0,23	0,23	0,23
2		1,00	0,80	0,69	0,69	0,57	0,46	0,46	0,43	0,45	0,39	0,38	0,38	0,38	0,41	0,41	0,35	0,37	0,39	0,37	0,32	0,28	0,29	0,23	0,23	0,23	0,18	0,23	0,20	0,23	0,23
3			1,00	0,86	0,75	0,57	0,51	0,49	0,46	0,47	0,42	0,46	0,44	0,44	0,44	0,46	0,40	0,39	0,39	0,32	0,32	0,28	0,29	0,23	0,20	0,23	0,18	0,28	0,23	0,25	0,20
4				1,00	0,83	0,68	0,62	0,59	0,57	0,55	0,50	0,54	0,54	0,46	0,46	0,49	0,40	0,41	0,41	0,34	0,34	0,30	0,32	0,28	0,28	0,30	0,25	0,35	0,28	0,33	0,23
5					1,00	0,73	0,57	0,54	0,49	0,47	0,42	0,46	0,51	0,46	0,49	0,54	0,43	0,44	0,46	0,41	0,39	0,35	0,29	0,30	0,28	0,28	0,25	0,35	0,30	0,33	0,28
6						1,00	0,78	0,73	0,70	0,63	0,61	0,51	0,51	0,46	0,46	0,46	0,40	0,41	0,49	0,41	0,39	0,35	0,32	0,30	0,33	0,30	0,25	0,35	0,33	0,30	0,20
7							1,00	0,86	0,81	0,71	0,68	0,59	0,54	0,49	0,49	0,44	0,38	0,46	0,44	0,41	0,41	0,38	0,37	0,33	0,35	0,38	0,35	0,38	0,38	0,38	0,30
8								1,00	0,89	0,76	0,74	0,64	0,59	0,54	0,51	0,49	0,40	0,49	0,44	0,41	0,39	0,38	0,37	0,30	0,33	0,38	0,35	0,38	0,35	0,35	0,28
9									1,00	0,82	0,79	0,69	0,62	0,54	0,51	0,49	0,40	0,41	0,41	0,37	0,34	0,33	0,32	0,28	0,28	0,35	0,30	0,35	0,33	0,30	0,23
10										1,00	0,92	0,79	0,69	0,62	0,59	0,54	0,43	0,51	0,49	0,46	0,39	0,38	0,39	0,35	0,30	0,38	0,35	0,43	0,33	0,35	0,28
11											1,00	0,79	0,72	0,62	0,59	0,54	0,45	0,46	0,44	0,41	0,34	0,35	0,37	0,35	0,30	0,38	0,33	0,40	0,30	0,33	0,28
12												1,00	0,85	0,72	0,67	0,64	0,53	0,46	0,46	0,41	0,39	0,40	0,39	0,40	0,33	0,43	0,38	0,45	0,33	0,33	0,30
13													1,00	0,79	0,74	0,69	0,55	0,44	0,44	0,41	0,39	0,40	0,37	0,40	0,33	0,43	0,38	0,43	0,33	0,35	0,30
14														1,00	0,79	0,72	0,60	0,51	0,51	0,44	0,51	0,48	0,44	0,40	0,33	0,38	0,33	0,40	0,33	0,33	0,33
15															1,00	0,79	0,65	0,59	0,54	0,49	0,46	0,45	0,41	0,45	0,38	0,35	0,30	0,38	0,30	0,33	0,30
16																1,00	0,83	0,66	0,63	0,59	0,54	0,50	0,44	0,50	0,40	0,38	0,30	0,35	0,30	0,30	0,28
17																	1,00	0,73	0,66	0,59	0,54	0,53	0,51	0,58	0,50	0,48	0,40	0,40	0,35	0,25	0,23
18																		1,00	0,85	0,78	0,63	0,60	0,56	0,53	0,48	0,45	0,45	0,40	0,33	0,35	0,30
19																			1,00	0,85	0,71	0,63	0,56	0,55	0,45	0,45	0,43	0,43	0,38	0,33	0,30
20																				1,00	0,80	0,73	0,66	0,60	0,55	0,45	0,48	0,40	0,38	0,38	0,38
21																					1,00	0,90	0,78	0,68	0,68	0,50	0,50	0,48	0,45	0,40	0,43
22																						1,00	0,88	0,75	0,75	0,58	0,55	0,45	0,45	0,38	0,40
23																							1,00	0,78	0,78	0,63	0,60	0,53	0,45	0,38	0,43
24																								1,00	0,85	0,75	0,68	0,58	0,50	0,38	0,40
25																									1,00	0,75	0,65	0,55	0,48	0,40	0,38
26																										1,00	0,80	0,65	0,58	0,48	0,38
27																											1,00	0,75	0,65	0,50	0,48
28																												1,00	0,73	0,60	0,53
29																													1,00	0,70	0,60
30																														1,00	0,75
31																															1,00

Table 9 - Transition matrix for Type 1, k = 40

The transition matrix represents the change in the lottery stock portfolio. This matrix has been created for all the six types and for the three cut-off rates. Here we present the first type with the cut-off rate 40. The results for other types with the same cut-off rate are very similar. The table shows that in each month what percentage of the lottery stocks have been part of the lottery stock portfolio in the previous month as

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**
1	1,00	0,96	0,96	0,89	0,82	0,75	0,72	0,62	0,59	0,60	0,60	0,53	0,53	0,57	0,53	0,50	0,45	0,38	0,44	0,47	0,50	0,47	0,47	0,45	0,39	0,35	0,35	0,32	0,26	0,26	0,67
2		1,00	0,96	0,89	0,86	0,79	0,72	0,62	0,59	0,60	0,60	0,53	0,53	0,57	0,53	0,50	0,45	0,38	0,44	0,47	0,50	0,47	0,47	0,45	0,39	0,35	0,35	0,32	0,26	0,29	0,67
3			1,00	0,93	0,86	0,79	0,76	0,66	0,62	0,63	0,63	0,57	0,53	0,60	0,57	0,53	0,48	0,41	0,47	0,50	0,53	0,50	0,50	0,48	0,42	0,39	0,39	0,35	0,29	0,26	0,71
4				1,00	0,93	0,82	0,76	0,66	0,62	0,67	0,67	0,60	0,57	0,63	0,60	0,57	0,52	0,44	0,50	0,53	0,56	0,53	0,53	0,52	0,45	0,42	0,42	0,39	0,32	0,29	0,75
5					1,00	0,89	0,79	0,69	0,66	0,70	0,70	0,60	0,60	0,67	0,63	0,57	0,52	0,47	0,53	0,56	0,59	0,56	0,56	0,55	0,48	0,45	0,45	0,42	0,35	0,35	0,71
6						1,00	0,83	0,72	0,69	0,73	0,73	0,63	0,63	0,70	0,67	0,60	0,55	0,53	0,59	0,59	0,66	0,63	0,63	0,61	0,55	0,52	0,52	0,45	0,39	0,39	0,71
7							1,00	0,90	0,86	0,83	0,83	0,73	0,77	0,80	0,77	0,73	0,68	0,59	0,66	0,66	0,72	0,66	0,66	0,61	0,55	0,55	0,55	0,52	0,42	0,39	0,75
8								1,00	0,93	0,87	0,87	0,77	0,80	0,77	0,77	0,70	0,68	0,63	0,66	0,63	0,69	0,63	0,63	0,58	0,55	0,55	0,55	0,55	0,45	0,39	0,67
9									1,00	0,93	0,90	0,83	0,87	0,80	0,77	0,73	0,71	0,66	0,69	0,63	0,69	0,63	0,63	0,58	0,55	0,55	0,55	0,52	0,45	0,39	0,67
10										1,00	0,97	0,90	0,90	0,87	0,83	0,77	0,74	0,69	0,72	0,66	0,72	0,66	0,66	0,61	0,58	0,58	0,58	0,55	0,48	0,42	0,71
11											1,00	0,90	0,90	0,87	0,83	0,77	0,74	0,69	0,72	0,66	0,69	0,63	0,63	0,58	0,55	0,58	0,58	0,55	0,48	0,42	0,67
12												1,00	0,93	0,90	0,87	0,80	0,81	0,72	0,75	0,69	0,72	0,69	0,69	0,65	0,61	0,65	0,65	0,61	0,55	0,48	0,67
13													1,00	0,90	0,87	0,80	0,81	0,72	0,75	0,69	0,72	0,66	0,66	0,61	0,58	0,61	0,61	0,58	0,52	0,48	0,63
14														1,00	0,97	0,87	0,84	0,78	0,84	0,78	0,81	0,72	0,72	0,68	0,61	0,65	0,65	0,61	0,55	0,52	0,71
15															1,00	0,87	0,84	0,78	0,84	0,78	0,81	0,72	0,72	0,68	0,61	0,65	0,65	0,65	0,58	0,55	0,67
16																1,00	0,94	0,81	0,88	0,78	0,78	0,69	0,69	0,65	0,58	0,61	0,61	0,61	0,55	0,52	0,67
17																	1,00	0,88	0,91	0,81	0,78	0,69	0,72	0,68	0,65	0,68	0,68	0,68	0,61	0,55	0,63
18																		1,00	0,94	0,84	0,84	0,78	0,81	0,77	0,74	0,77	0,77	0,74	0,68	0,61	0,63
19																			1,00	0,88	0,88	0,78	0,81	0,77	0,71	0,74	0,74	0,71	0,65	0,61	0,67
20																				1,00	0,91	0,84	0,88	0,84	0,81	0,81	0,81	0,81	0,74	0,71	0,71
21																					1,00	0,91	0,91	0,87	0,81	0,81	0,81	0,74	0,65	0,61	0,79
22																						1,00	0,97	0,94	0,87	0,84	0,87	0,81	0,74	0,71	0,75
23																							1,00	0,97	0,90	0,87	0,87	0,81	0,74	0,71	0,75
24																								1,00	0,94	0,87	0,87	0,81	0,74	0,71	0,75
25																									1,00	0,94	0,94	0,87	0,81	0,74	0,67
26																										1,00	0,97	0,90	0,81	0,74	0,67
27																											1,00	0,94	0,84	0,77	0,67
28																												1,00	0,87	0,81	0,63
29																													1,00	0,90	0,63
30																														1,00	0,54
31																															1,00

Table 10 - Transition matrix for Type 1, k = 30
The transition matrix represents the change in the lottery stock portfolio. This matrix has been created for all the six types and for the three cut-off rates. Here we present the first type with the cut-off rate 30. The results for other types with the same cut-off rate are very similar. The table shows that in each month what percentage of the lottery stocks have been part of the lottery stock portfolio in the previous month as well.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**
1	1,00	0,94	0,89	0,89	0,83	0,74	0,68	0,53	0,53	0,53	0,53	0,55	0,55	0,60	0,50	0,50	0,50	0,48	0,48	0,48	0,48	0,43	0,43	0,40	0,40	0,35	0,35	0,35	0,35	0,35	0,63
2		1,00	0,94	0,94	0,89	0,79	0,68	0,53	0,53	0,53	0,53	0,55	0,55	0,60	0,50	0,50	0,50	0,48	0,48	0,48	0,48	0,43	0,43	0,40	0,40	0,35	0,35	0,35	0,35	0,35	0,63
3			1,00	1,00	0,94	0,79	0,68	0,58	0,58	0,58	0,58	0,60	0,55	0,60	0,50	0,50	0,50	0,48	0,48	0,48	0,48	0,43	0,43	0,40	0,40	0,35	0,35	0,35	0,35	0,35	0,69
4				1,00	0,94	0,79	0,68	0,58	0,58	0,58	0,58	0,60	0,55	0,60	0,50	0,50	0,50	0,48	0,48	0,48	0,48	0,43	0,43	0,40	0,40	0,35	0,35	0,35	0,35	0,35	0,69
5					1,00	0,84	0,74	0,63	0,63	0,63	0,63	0,60	0,55	0,60	0,50	0,50	0,50	0,48	0,48	0,48	0,52	0,48	0,48	0,45	0,45	0,40	0,40	0,40	0,40	0,40	0,69
6						1,00	0,84	0,68	0,68	0,68	0,68	0,65	0,60	0,65	0,55	0,55	0,55	0,52	0,48	0,48	0,52	0,48	0,48	0,45	0,50	0,45	0,45	0,45	0,45	0,45	0,63
7							1,00	0,79	0,74	0,68	0,68	0,65	0,60	0,65	0,55	0,55	0,55	0,52	0,48	0,48	0,52	0,48	0,48	0,45	0,50	0,45	0,45	0,45	0,40	0,40	0,56
8								1,00	0,89	0,84	0,84	0,70	0,70	0,65	0,60	0,60	0,60	0,57	0,52	0,52	0,57	0,52	0,52	0,50	0,55	0,50	0,50	0,50	0,45	0,45	0,50
9									1,00	0,95	0,95	0,80	0,80	0,75	0,70	0,70	0,65	0,67	0,62	0,57	0,62	0,57	0,57	0,55	0,60	0,55	0,55	0,55	0,50	0,50	0,50
10										1,00	1,00	0,85	0,85	0,80	0,75	0,75	0,70	0,71	0,67	0,62	0,67	0,62	0,62	0,60	0,65	0,60	0,60	0,60	0,55	0,55	0,56
11											1,00	0,85	0,85	0,80	0,75	0,75	0,70	0,71	0,67	0,62	0,67	0,62	0,62	0,60	0,65	0,60	0,60	0,60	0,55	0,55	0,56
12												1,00	0,90	0,95	0,85	0,85	0,80	0,81	0,76	0,71	0,71	0,67	0,62	0,60	0,65	0,60	0,60	0,60	0,55	0,55	0,56
13													1,00	0,95	0,90	0,90	0,85	0,86	0,81	0,76	0,76	0,71	0,67	0,65	0,70	0,65	0,65	0,65	0,60	0,60	0,56
14														1,00	0,90	0,90	0,85	0,86	0,81	0,76	0,76	0,71	0,67	0,65	0,70	0,65	0,65	0,65	0,60	0,60	0,56
15															1,00	0,95	0,90	0,95	0,90	0,81	0,81	0,76	0,71	0,70	0,75	0,70	0,70	0,70	0,65	0,65	0,56
16																1,00	0,90	0,95	0,86	0,86	0,81	0,76	0,71	0,70	0,75	0,70	0,70	0,70	0,65	0,65	0,56
17																	1,00	0,90	0,81	0,76	0,71	0,67	0,62	0,60	0,65	0,60	0,60	0,60	0,55	0,55	0,50
18																		1,00	0,90	0,86	0,81	0,76	0,71	0,70	0,75	0,70	0,70	0,70	0,65	0,65	0,56
19																			1,00	0,90	0,90	0,86	0,81	0,75	0,75	0,75	0,75	0,75	0,70	0,70	0,56
20																				1,00	0,90	0,86	0,81	0,75	0,75	0,75	0,75	0,75	0,70	0,70	0,63
21																					1,00	0,95	0,90	0,85	0,85	0,85	0,85	0,85	0,80	0,80	0,56
22																						1,00	0,95	0,90	0,85	0,90	0,90	0,90	0,85	0,85	0,56
23																							1,00	0,95	0,90	0,95	0,95	0,90	0,85	0,85	0,56
24																								1,00	0,95	0,95	0,95	0,90	0,85	0,85	0,56
25																									1,00	0,95	0,95	0,90	0,85	0,85	0,50
26																										1,00	1,00	0,95	0,90	0,90	0,50
27																											1,00	0,95	0,90	0,90	0,50
28																												1,00	0,90	0,90	0,50
29																													1,00	0,95	0,56
30																														1,00	0,56
31																															1,00

Figure 6: Time series of OMXS30 index and net buy imbalance of lottery stocks for type 1, k = 50

The graph shows the movement of the OMXS30 index and the time variation of individuals' net buy imbalance of lottery stocks for type 1 and k = 50 between July 2006 and January 2009. The graphs for other types with the same cut-off rate are very similar.

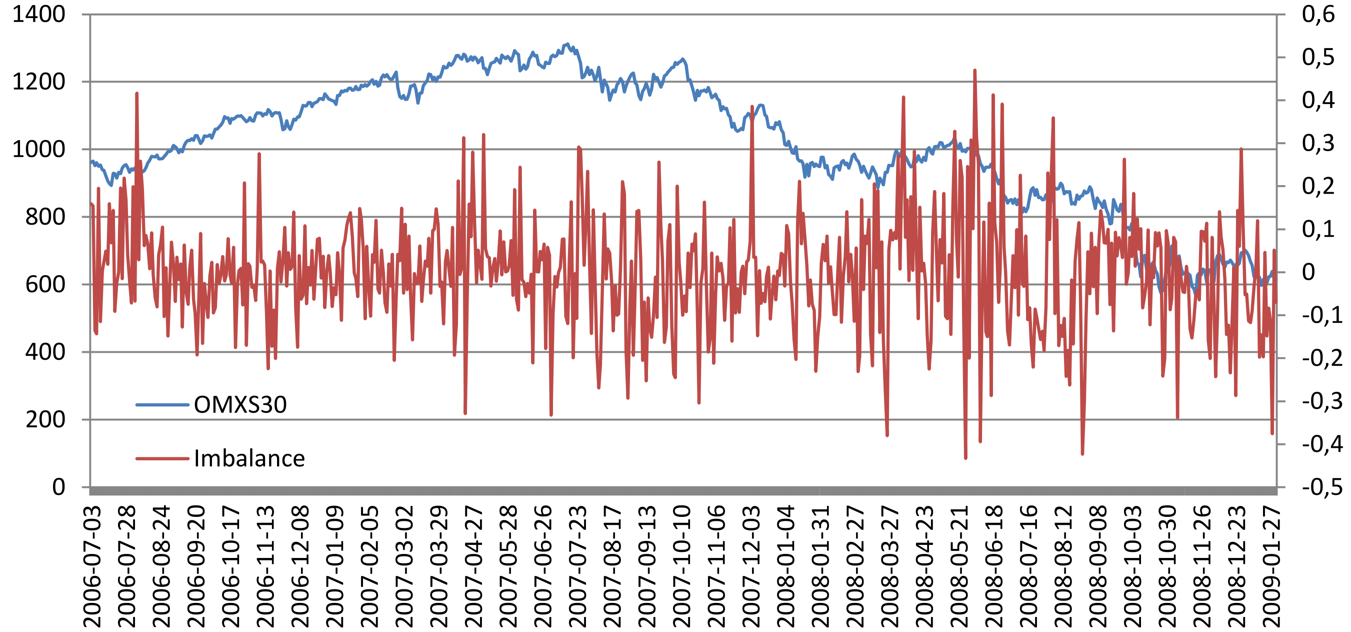

Figure 7: Time series of OMXS30 index and net buy imbalance of lottery stocks for type 1, k = 40

The graph shows the movement of the OMXS30 index and the time variation of individuals' net buy imbalance of lottery stocks for type 1 and k = 40 between July 2006 and January 2009. The graphs for other types with the same cut-off rate are very similar.

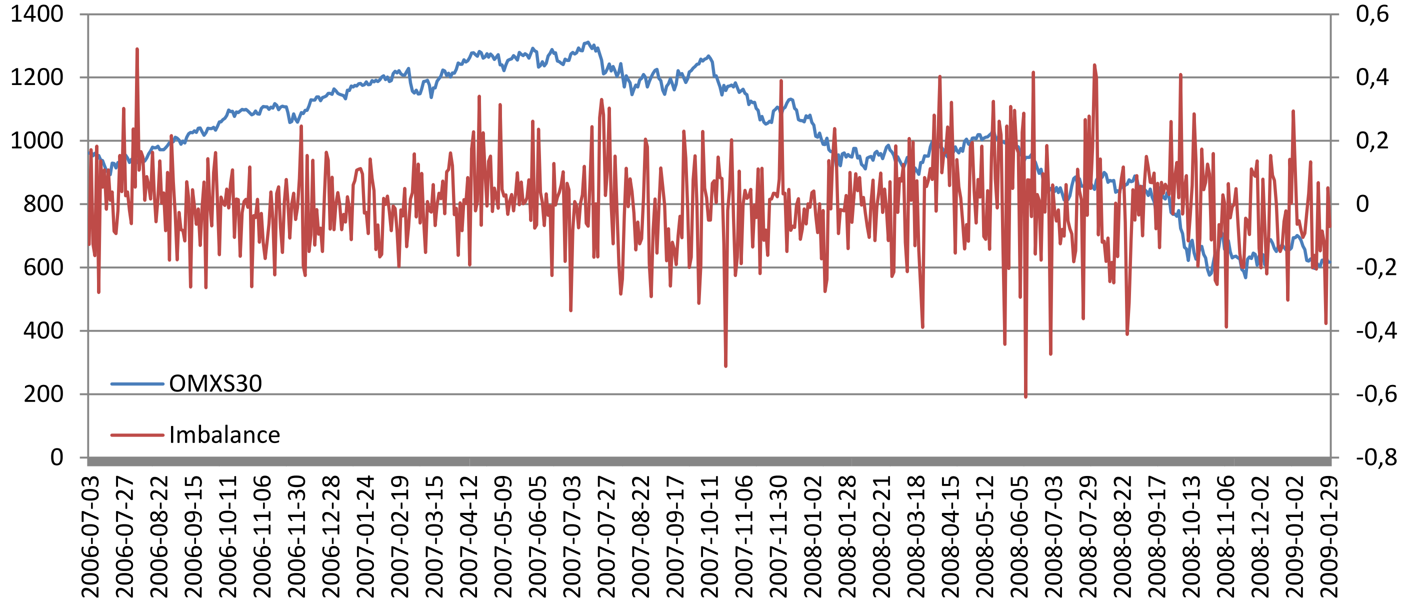

Figure 8: Time series of OMXS30 index and net buy imbalance of lottery stocks for type 1, k = 30

The graph shows the movement of the OMXS30 index and the time variation of individuals' net buy imbalance of lottery stocks for type 1 and k = 30 between July 2006 and January 2009. The graphs for other types with the same cut-off rate are very similar.

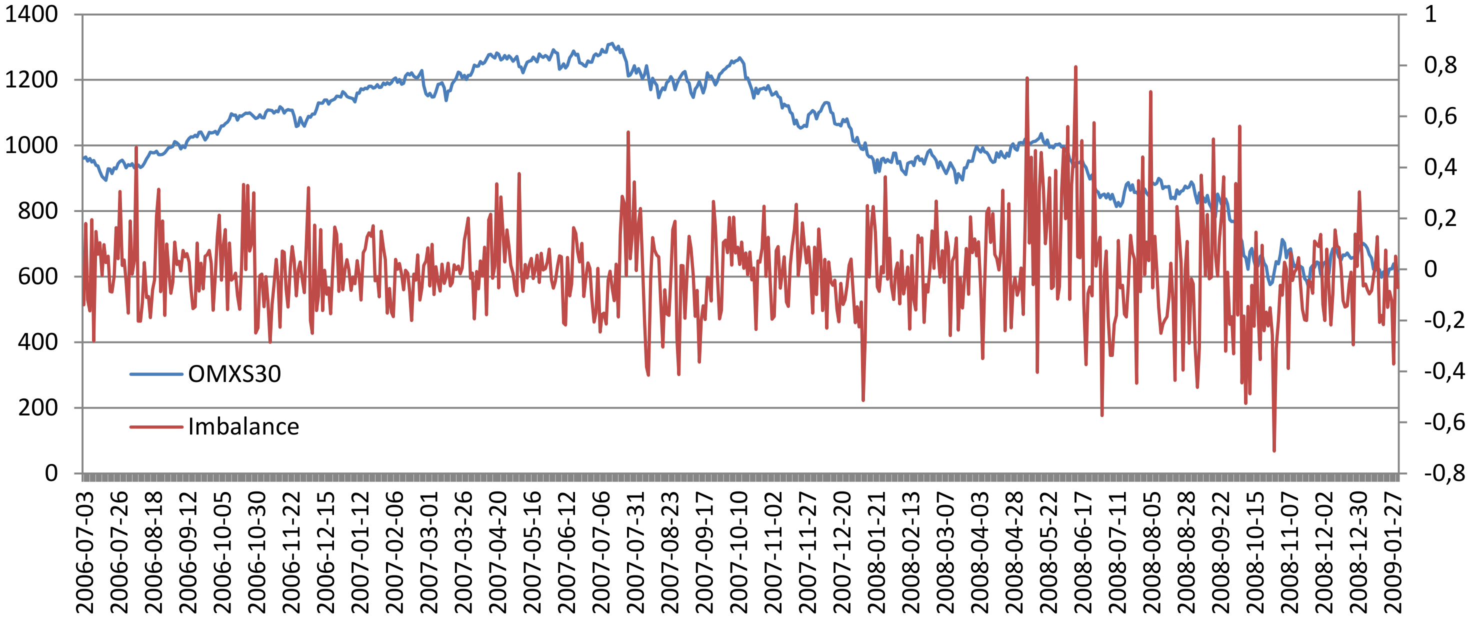

Table 11

*Tables 11.1 and 11.2 show the results of regression 5 for each type of lottery portfolio first for k=40 and then for k=30. The dependent variable is the return of the lottery portfolio. The independent variables are the return of the OMXS30 and the net buy imbalance of individual investors in the lottery portfolio. In the rolling regression every time one month is added for the returns in order to see the long-time effects of the imbalance at a certain point of time. Given are the coefficients and the t-statistics in parenthesis. Coefficients with statistical significance (p-values) are marked with stars. *=significance level at 10%, **=significance level at 5%, ***=significance level at 1%*

Table 11.1

k=40

	Type 1				Type 2			
t	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0010	0,5276***	0,0136**	0,2786	-0,0008	0,5005***	0,0111**	0,3528
	(0,0922)	(0,0000)	(0,0024)		(0,0917)	(0,0000)	(0,0082)	
1	-0,0106	0,7311***	-0,1082	0,2735	-0,0134	0,7775***	-0,0903	0,4223
	(-0,8180)	(2,7161)	(-2,3690)		(-1,3818)	(3,8650)	(-2,6387)	
2	-0,0030	1,1181***	-0,1018	0,4479	-0,0185	1,0778***	-0,1195	0,6330
	(-0,1571)	(4,5217)	(-1,5111)		(-1,3564)	(6,1921)	(-2,5126)	
3	0,0123	1,2290***	-0,0472	0,5918	-0,0043	1,1318***	-0,0833	0,7170
	(0,5467)	(5,9493)	(-0,6081)		(-0,2606)	(7,4100)	(-1,4472)	
4	0,0284**	1,2498***	-0,0301	0,6587	0,0074**	1,1856***	-0,0804	0,8123
	(1,1496)	(7,0355)	(-0,3619)		(0,4565)	(10,1310)	(-1,4647)	
5	0,0364***	1,3414***	-0,0913	0,7640	0,0083***	1,2657***	-0,1269	0,8471
	(1,4774)	(9,0752)	(-1,1110)		(0,4541)	(11,6376)	(-2,0926)	
6	0,0483***	1,3545***	-0,0009	0,7958	0,0203***	1,2400***	-0,0537*	0,8138
	(1,8087)	(9,9547)	(-0,0104)		(0,8648)	(10,3955)	(-0,6975)	
7	0,0663***	1,3470***	0,0494	0,7937	0,0311***	1,2581***	-0,0061	0,8395
	(2,1653)	(9,7101)	(0,4707)		(1,2481)	(11,2623)	(-0,0701)	
8	0,0849***	1,3468***	0,0210	0,8277	0,0411***	1,2628***	0,0041*	0,9093
	(2,7454)	(10,6063)	(0,2039)		(2,0082)	(15,2315)	(0,0593)	
9	0,0830***	1,2880***	-0,1391	0,8867	0,0315***	1,2056***	-0,0960	0,9400
	(3,1926)	(12,7276)	(-1,4755)		(1,8131)	(18,0284)	(-1,5259)	
10	0,0774***	1,2653***	-0,1532	0,9199	0,0339***	1,2183***	-0,1062*	0,9098
	(3,4042)	(15,0636)	(-1,9169)		(1,4428)	(14,2026)	(-1,2890)	
11	0,0845***	1,2432***	-0,1162	0,9078	0,0320***	1,2157***	-0,0993	0,9241
	(3,3453)	(14,0868)	(-1,2511)		(1,4165)	(15,6376)	(-1,2102)	
12	0,0822***	1,2733***	-0,1209	0,9394	0,0363***	1,2184***	-0,1253	0,9542
	(3,7700)	(17,2021)	(-1,5367)		(1,9822)	(19,9361)	(-1,9148)	
13	0,1070***	1,2628***	0,0248	0,9536	0,0547***	1,2047***	-0,0715	0,9524
	(5,2437)	(18,8418)	(0,3377)		(2,7635)	(18,8690)	(-1,0114)	

	Type 3				Type 4			
t	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0012 (0,0534)	0,5124*** (0,0000)	0,0095* (0,0220)	0,2737	-0,0002 (0,7547)	0,5403*** (0,0000)	0,0121** (0,0038)	0,3485
1	-0,0185 (-1,7697)	0,6523*** (3,0001)	-0,1006 (-2,7148)	0,3316	0,0039 (0,5038)	1,0509*** (6,4952)	-0,0405 (-1,4528)	0,6206
2	-0,0250 (-1,4993)	0,9570*** (4,4782)	-0,1271 (-2,1738)	0,4686	0,0119 (0,8771)	1,1544*** (6,6692)	-0,0922 (-1,9246)	0,6491
3	-0,0130 (-0,6147)	1,0779*** (5,5499)	-0,0621 (-0,8472)	0,5623	0,0264 (1,5371)	1,1925*** (7,5204)	-0,1195 (-1,9730)	0,7308
4	0,0007 (0,0316)	1,1291*** (6,8491)	-0,0447 (-0,5773)	0,6475	0,0400* (2,7027)	1,3860*** (12,9642)	-0,1382 (-2,7227)	0,8800
5	0,0115 (0,4722)	1,2440*** (8,4755)	-0,0959 (-1,1706)	0,7380	0,0526*** (3,4415)	1,4999*** (16,3353)	-0,1773 (-3,4200)	0,9170
6	0,0297** (1,0414)	1,2873*** (8,8420)	-0,0194 (-0,2066)	0,7539	0,0746*** (3,7904)	1,4929*** (14,8538)	-0,1068 (-1,6253)	0,9009
7	0,0445*** (1,2778)	1,2832*** (8,1030)	0,0297 (0,2475)	0,7262	0,0971*** (4,4595)	1,5231*** (15,5003)	-0,0792 (-1,0176)	0,9095
8	0,0668*** (1,9677)	1,3009*** (9,2920)	0,0199 (0,1748)	0,7857	0,1191*** (4,8466)	1,5686*** (15,6087)	-0,1680 (-1,9623)	0,9150
9	0,0594*** (2,0049)	1,2487*** (10,7998)	-0,1398 (-1,2958)	0,8481	0,1315*** (4,9475)	1,5376*** (14,9571)	-0,2620 (-2,6965)	0,9176
10	0,0575*** (2,0347)	1,2066*** (11,5211)	-0,1436 (-1,4377)	0,8689	0,1302*** (4,0860)	1,5518*** (13,2555)	-0,2556 (-2,2612)	0,9000
11	0,0635*** (2,1025)	1,1854*** (11,1515)	-0,1271 (-1,1358)	0,8598	0,1321*** (3,6326)	1,5923*** (12,5514)	-0,2813 (-2,0951)	0,8875
12	0,0670*** (2,6107)	1,1845*** (13,4692)	-0,0818 (-0,8743)	0,9048	0,1402*** (3,6968)	1,5771*** (12,2278)	-0,2493 (-1,8081)	0,8859
13	0,0873*** (3,4817)	1,1809*** (14,1780)	0,0312 (0,3412)	0,9214	0,1655*** (3,8451)	1,5895*** (11,2211)	-0,1919 (-1,2260)	0,8745

	Type 5				Type 6			
t	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0006 (0,2394)	0,5225*** (0,0000)	0,0100*** (0,0177)	0,3602	-0,0007 (0,2034)	0,5025*** (0,0000)	0,0064* (0,1898)	0,2957
1	-0,0090 (-0,9058)	0,9137*** (4,4643)	-0,0732 (-2,0531)	0,4529	-0,0131 (-0,9990)	0,9464*** (3,4973)	-0,0943 (-2,0460)	0,3459
2	-0,0119 (-0,9590)	0,9769*** (6,2104)	-0,0955 (-2,1706)	0,6226	-0,0191 (-1,2555)	1,0264*** (5,3124)	-0,1426 (-2,6987)	0,5736
3	-0,0072 (-0,5193)	0,9936*** (7,7785)	-0,0850 (-1,7234)	0,7369	-0,0128 (-0,7144)	0,9972*** (6,0817)	-0,1235 (-1,9945)	0,6504
4	-0,0097 (-0,7397)	1,0842*** (11,4860)	-0,1086** (-2,3969)	0,8514	-0,0060 (-0,3518)	1,1000*** (8,9813)	-0,1391 (-2,4198)	0,7838
5	-0,0078 (-0,4842)	1,1953*** (12,4310)	-0,1860 (-3,3884)	0,8676	0,0007 (0,0378)	1,2134*** (11,2719)	-0,1840 (-3,0621)	0,8435
6	0,0062 (0,2922)	1,2176*** (11,2831)	-0,1352 (-1,8961)	0,8426	0,0057** (0,2387)	1,2097*** (10,0333)	-0,1288 (-1,6532)	0,8086
7	0,0096** (0,4219)	1,2252*** (11,9544)	-0,1226 (-1,5200)	0,8583	0,0050** (0,1951)	1,2013*** (10,4121)	-0,1208 (-1,3353)	0,8208
8	0,0095** (0,4187)	1,2202*** (13,2900)	-0,1432 (-1,8394)	0,8868	0,0064** (0,2576)	1,1921*** (11,8855)	-0,1304 (-1,5390)	0,8618
9	-0,0007*** (-0,0333)	1,2032*** (14,9270)	-0,2022 (-2,6383)	0,9182	-0,0030*** (-0,1400)	1,1620*** (14,3142)	-0,2019 (-2,6311)	0,9119
10	0,0010*** (0,0383)	1,2030*** (12,7085)	-0,1881 (-2,0462)	0,8924	-0,0093*** (-0,3603)	1,1642*** (12,4154)	-0,2166 (-2,3921)	0,8895
11	0,0082*** (0,3258)	1,2056*** (13,9044)	-0,2128 (-2,3160)	0,9069	-0,0041*** (-0,1499)	1,1729*** (12,2978)	-0,2537 (-2,5249)	0,8849
12	0,0067*** (0,2891)	1,1762*** (15,1244)	-0,2245 (-2,6849)	0,9229	-0,0025*** (-0,0937)	1,1548*** (13,1149)	-0,2635 (-2,7994)	0,9001
13	0,0219*** (0,7473)	1,1708*** (12,2931)	-0,1666 (-1,5734)	0,8928	0,0091*** (0,3031)	1,1375*** (11,6788)	-0,1947 (-1,8074)	0,8821

Table 11.2

k=30

t	Type 1 alpha	Type 1 market return	Type 1 lottery imbalance	Type 1 adj. Rsquared	Type 2 alpha	Type 2 market return	Type 2 lottery imbalance	Type 2 adj. Rsquared
0	-0,0005	0,5499***	0,0090**	0,2089	-0,0014	0,5203***	0,0104**	0,2365
	(0,5342)	(0,0000)	(0,0398)		(0,0361)	(0,0000)	(0,0206)	
1	-0,0028	0,5137**	-0,0692	0,0360	-0,0204	0,5370***	-0,0830	0,1083
	(-0,1587)	(1,4070)	(-1,0355)		(-1,3565)	(1,7365)	(-1,5233)	
2	0,0088	0,9630***	-0,0664	0,2638	-0,0303	0,9847***	-0,0896	0,3549
	(0,3739)	(3,1805)	(-0,7464)		(-1,4682)	(3,7480)	(-1,2053)	
3	0,0275	0,9990***	0,0682	0,2934	-0,0269	1,2712***	-0,0475	0,6504
	(0,8943)	(3,5108)	(0,5910)		(-1,2921)	(6,6522)	(-0,6366)	
4	0,0425	1,1871***	0,1250	0,5281	-0,0182	1,4288***	-0,0697	0,8369
	(1,4115)	(5,4553)	(1,1389)		(-1,0230)	(11,1962)	(-1,1245)	
5	0,0443*	1,2870***	0,1161	0,7018	-0,0106	1,4595***	-0,1534	0,8564
	(1,5986)	(7,7472)	(1,1652)		(-0,5254)	(12,0885)	(-2,2004)	
6	0,0537*	1,3517***	0,1823	0,7435	0,0025**	1,4563***	-0,0765	0,8549
	(1,7477)	(8,6055)	(1,6714)		(0,1036)	(12,0001)	(-0,9426)	
7	0,0709**	1,4277***	0,2570	0,8497	0,0261**	1,4656***	-0,0072	0,9016
	(2,5944)	(11,5904)	(2,4903)		(1,1866)	(14,8558)	(-0,0914)	
8	0,0788**	1,4413***	0,2335	0,8913	0,0366***	1,4413***	-0,0384	0,9046
	(3,0704)	(13,7051)	(2,4796)		(1,5297)	(14,7705)	(-0,4621)	
9	0,0789**	1,4928***	0,1957	0,9021	0,0260***	1,4043***	-0,0912	0,9255
	(2,9316)	(14,3008)	(1,9342)		(1,1522)	(16,0833)	(-1,1073)	
10	0,0816**	1,4406***	0,1614	0,9211	0,0345***	1,4035***	-0,1281	0,9191
	(3,2650)	(15,7232)	(1,7740)		(1,3570)	(15,0953)	(-1,4245)	
11	0,0876**	1,4322***	0,0972	0,8926	0,0487***	1,4187***	-0,1663	0,8956
	(2,7594)	(12,8802)	(0,8221)		(1,5595)	(13,1105)	(-1,4821)	
12	0,0954**	1,4844***	0,0722	0,8917	0,0557***	1,4377***	-0,1819	0,9146
	(2,7082)	(12,3783)	(0,5595)		(1,8708)	(14,3371)	(-1,7336)	
13	0,1250**	1,4804***	0,1931	0,9142	0,0691***	1,3633***	-0,0457	0,8780
	(3,6682)	(13,2054)	(1,5453)		(1,8690)	(11,3466)	(-0,3516)	

t	Type 3				Type 4			
	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0009	0,5166***	0,0040	0,2114	-0,0005	0,4847***	0,0090**	0,1931
	(0,2414)	(0,0000)	(0,3523)		(0,4650)	(0,0000)	(0,0511)	
1	-0,0157	0,6394***	-0,1179	0,1555	-0,0100	0,6643**	-0,0855	0,1559
	(-0,9498)	(1,8654)	(-1,9015)		(-0,6840)	(2,1890)	(-1,6628)	
2	-0,0075	0,9657***	-0,0990	0,2896	0,0002	0,8429***	-0,1029	0,3310
	(-0,3201)	(3,2231)	(-1,1380)		(0,0097)	(3,4960)	(-1,5696)	
3	0,0057	1,0219***	-0,0246	0,3780	0,0056	1,0017***	-0,0763	0,4958
	(0,2052)	(3,9658)	(-0,2383)		(0,2470)	(4,8077)	(-0,9760)	
4	0,0267	1,0989***	0,0537	0,4440	0,0182	1,1868***	-0,0586	0,7338
	(0,8229)	(4,6858)	(0,4594)		(0,9152)	(8,3026)	(-0,8783)	
5	0,0443	1,1992***	0,0700	0,6329	0,0264	1,2832***	-0,1063	0,7969
	(1,4837)	(6,6904)	(0,6591)		(1,2293)	(9,9559)	(-1,4869)	
6	0,0610**	1,2790***	0,1416	0,7059	0,0517**	1,3844***	-0,0279	0,8018
	(1,9150)	(7,8587)	(1,2679)		(1,9249)	(10,1222)	(-0,3175)	
7	0,0843**	1,3202***	0,2008	0,7281	0,0758***	1,4722***	0,0522*	0,8058
	(2,3280)	(8,0694)	(1,4867)		(2,3466)	(10,0718)	(0,4710)	
8	0,0975**	1,3642***	0,1928	0,8169	0,1026***	1,5068***	0,0866	0,8657
	(2,9809)	(10,1661)	(1,6281)		(3,4254)	(12,2292)	(0,8660)	
9	0,0988***	1,3561***	0,0743	0,8148	0,1047***	1,4823***	0,0376	0,8670
	(2,7995)	(9,8734)	(0,5520)		(3,2844)	(11,9563)	(0,3201)	
10	0,0941***	1,3100***	0,0198	0,8595	0,1116***	1,4520***	0,0778*	0,8841
	(2,9989)	(11,3407)	(0,1707)		(3,5955)	(12,7056)	(0,7017)	
11	0,1059***	1,2459***	0,0357	0,7863	0,1313***	1,4797***	0,0447*	0,8602
	(2,5816)	(8,6853)	(0,2321)		(3,4584)	(11,1444)	(0,3147)	
12	0,1139***	1,3613***	-0,0094	0,8452	0,1625***	1,5147***	0,0556*	0,7991
	(2,9031)	(10,2349)	(-0,0652)		(3,1623)	(8,6713)	(0,2940)	
13	0,1494***	1,4174***	0,0850	0,8666	0,2203***	1,6174***	0,1836**	0,7848
	(3,6626)	(10,6220)	(0,5696)		(3,5091)	(7,8302)	(0,7952)	

t	Type 5				Type 6			
	alpha	market return	lottery imbalance	adj. Rsquared	alpha	market return	lottery imbalance	adj. Rsquared
0	-0,0010	0,5289***	0,0095*	0,2752	-0,0007	0,5271***	0,0100*	0,2638
	(0,0940)	(0,0000)	(0,0259)		(0,2444)	(0,0000)	(0,0251)	
1	-0,0219	0,6715***	-0,0827	0,1856	-0,0132	0,5932***	-0,0919	0,1530
	(-1,5505)	(2,3237)	(-1,6237)		(-0,8926)	(1,9547)	(-1,7175)	
2	-0,0437	1,1285***	-0,1076	0,4518	-0,0320	1,1205***	-0,1077	0,3999
	(-2,1701)	(4,4319)	(-1,4935)		(-1,4614)	(4,0196)	(-1,3636)	
3	-0,0305	1,3162***	-0,0170	0,6500	-0,0138	1,2308***	-0,0548	0,5562
	(-1,4208)	(6,6934)	(-0,2212)		(-0,5594)	(5,4046)	(-0,6152)	
4	-0,0130	1,4395***	-0,0609	0,7950	-0,0004	1,3614***	-0,0790	0,7323
	(-0,6271)	(9,7062)	(-0,8461)		(-0,0170)	(8,1153)	(-0,9697)	
5	0,0021*	1,4775***	-0,1834	0,8220	0,0153*	1,4228***	-0,1861	0,7821
	(0,0872)	(10,5268)	(-2,2627)		(0,5940)	(9,2646)	(-2,0964)	
6	0,0258***	1,4916***	-0,1341	0,8065	0,0293***	1,4233***	-0,1314	0,7582
	(0,8716)	(9,9670)	(-1,3406)		(0,9029)	(8,6346)	(-1,1914)	
7	0,0397***	1,5241***	-0,1328	0,8293	0,0393***	1,4348***	-0,1391	0,7836
	(1,2335)	(10,6968)	(-1,1570)		(1,1267)	(9,2174)	(-1,1107)	
8	0,0591***	1,5061***	-0,1613	0,8542	0,0480***	1,4163***	-0,1962	0,8245
	(1,8052)	(11,4559)	(-1,4211)		(1,3954)	(10,1741)	(-1,6358)	
9	0,0472***	1,4116***	-0,2471	0,8928	0,0438***	1,3627***	-0,2507	0,8614
	(1,6193)	(12,7056)	(-2,3308)		(1,3512)	(10,9161)	(-2,0993)	
10	0,0457***	1,4114***	-0,2461	0,9057	0,0506***	1,3678***	-0,2419	0,8701
	(1,5817)	(13,5549)	(-2,4157)		(1,5166)	(11,2669)	(-2,0327)	
11	0,0597***	1,4209***	-0,2776	0,9044	0,0655***	1,3843***	-0,2637	0,8765
	(1,9496)	(13,6233)	(-2,5216)		(1,9146)	(11,7831)	(-2,1281)	
12	0,0729***	1,3887***	-0,2580	0,9012	0,0751***	1,3363***	-0,2453	0,8565
	(2,2890)	(13,2097)	(-2,2865)		(1,9976)	(10,6992)	(-1,8346)	
13	0,0918***	1,3442***	-0,1639	0,8998	0,0950***	1,3255***	-0,1749	0,8564
	(2,7687)	(12,7661)	(-1,4037)		(2,3921)	(10,4552)	(-1,2504)	

Table 12

Tables 12.1 and 12.2 show the results of regression 7 for each type of lottery portfolio first for k=40 and then for k=30. The independent variable is the return of the non-lottery portfolio. The dependent variable is the return of the lottery portfolio. In the rolling regression every time one month is added for the returns in order to see the long-time performance of the two portfolios compared to each other. Given are the coefficients and the t-statistics in parenthesis. Coefficients with statistical significance (p-values) are marked with stars.=significance level at 10%, **=significance level at 5%, ***=significance level at 1%*

Table 12.1

k=40

	Type 1			Type 2			Type 3		
t	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared	alpha	non-lottery portfolio return	adj. Rsquared
1	0,0033 (0,3133)	0,9165*** (5,8186)	0,5227	0,0070 (0,7700)	0,9210*** (6,8149)	0,6023	-0,0008 (-0,0996)	0,7074*** (5,8742)	0,5276
2	0,0144 (0,4309)	1,4618*** (0,0000)	0,5014	0,0133 (0,3680)	1,5337*** (0,0000)	0,6318	0,0017 (0,9048)	1,1469*** (0,0000)	0,4933
3	0,0140 (0,5734)	1,4855*** (0,0003)	0,3686	0,0078 (0,7049)	1,6146*** (0,0000)	0,5039	-0,0021 (0,9220)	1,2106*** (0,0006)	0,3331
4	0,0113 (0,7143)	1,4814*** (0,0037)	0,2539	-0,0094 (0,7134)	1,7331*** (0,0001)	0,4116	-0,0057 (0,8292)	1,2521*** (0,0043)	0,2456
5	0,0074 (0,8429)	1,4692** (0,0395)	0,1251	-0,0191 (0,5556)	1,9399** (0,0032)	0,2707	-0,0072 (0,8309)	1,2396* (0,0528)	0,1075
6	0,0005 (0,9905)	1,1821 (0,2055)	0,0270	-0,0310 (0,4299)	2,1394** (0,0128)	0,1996	-0,0060 (0,8888)	1,0126 (0,2468)	0,0161
7	-0,0035 (0,9468)	0,8485 (0,4199)	-0,0137	-0,0380 (0,4091)	1,8179* (0,0587)	0,1097	-0,0106 (0,8327)	0,6676 (0,5043)	-0,0230
8	-0,0059 (0,9200)	0,4925 (0,6748)	-0,0369	-0,0472 (0,3823)	1,5664 (0,1557)	0,0481	-0,0147 (0,7975)	0,3525 (0,7559)	-0,0408
9	-0,0068 (0,9162)	-0,1939 (0,8818)	-0,0465	-0,0524 (0,3901)	0,9879 (0,4266)	-0,0158	-0,0195 (0,7550)	-0,3264 (0,7946)	-0,0442
10	-0,0236 (0,7226)	0,8093 (0,5471)	-0,0307	-0,0589 (0,3670)	1,8468 (0,1736)	0,0450	-0,0330 (0,6050)	0,6304 (0,6240)	-0,0371
11	-0,0337 (0,6096)	1,2686 (0,3398)	-0,0021	-0,0644 (0,3336)	2,1955 (0,1114)	0,0820	-0,0419 (0,5080)	1,1372 (0,3696)	-0,0078
12	-0,0655 (0,3413)	1,6656 (0,2238)	0,0300	-0,0859 (0,1978)	2,3962* (0,0776)	0,1165	-0,0690 (0,2855)	1,5461 (0,2260)	0,0292

t	Type 4 alpha	Type 4 non-lottery portfolio return	Type 4 adj. Rsquared	Type 5 alpha	Type 5 non-lottery portfolio return	Type 5 adj. Rsquared	Type 6 alpha	Type 6 non-lottery portfolio return	Type 6 adj. Rsquared
1	0,0069 (0,8370)	0,9001*** (7,2918)	0,6349	0,0030 (0,4187)	0,8568*** (8,0775)	0,6817	0,0087 (0,9458)	0,8478*** (6,1898)	0,5543
2	0,0143 (0,4036)	1,4522*** (0,0000)	0,5349	0,0014 (0,9201)	1,3247*** (0,0000)	0,6002	0,0079 (0,5799)	1,3537*** (0,0000)	0,5869
3	0,0164 (0,5482)	1,6351*** (0,0003)	0,3726	-0,0063 (0,7558)	1,4308*** (0,0000)	0,4498	0,0029 (0,8948)	1,4258*** (0,0001)	0,4157
4	0,0094 (0,7860)	1,8539*** (0,0015)	0,3014	-0,0194 (0,4523)	1,5676*** (0,0004)	0,3638	-0,0056 (0,8315)	1,6829*** (0,0002)	0,3897
5	0,0066 (0,8778)	2,1389** (0,0118)	0,1971	-0,0231 (0,4800)	1,9613*** (0,0029)	0,2758	-0,0090 (0,7802)	2,0818*** (0,0016)	0,3069
6	0,0058 (0,9113)	2,4130** (0,0299)	0,1476	-0,0204 (0,6063)	2,1923** (0,0112)	0,2079	-0,0131 (0,7329)	2,2539*** (0,0079)	0,2284
7	0,0121 (0,8389)	2,0637* (0,0934)	0,0792	-0,0212 (0,6254)	1,9010** (0,0372)	0,1395	-0,0174 (0,6819)	1,9832** (0,0277)	0,1586
8	0,0240 (0,7254)	1,8716 (0,1795)	0,0385	-0,0260 (0,5742)	1,6180* (0,0895)	0,0857	-0,0256 (0,5727)	1,7777* (0,0600)	0,1131
9	0,0336 (0,6614)	1,2117 (0,4415)	-0,0178	-0,0337 (0,5162)	1,1572 (0,2783)	0,0107	-0,0303 (0,5335)	1,2981 (0,1991)	0,0333
10	0,0301 (0,7021)	1,9792 (0,2244)	0,0265	-0,0406 (0,4458)	1,9274* (0,0847)	0,0984	-0,0367 (0,4407)	2,0353** (0,0452)	0,1451
11	0,0179 (0,8223)	2,4563 (0,1374)	0,0657	-0,0472 (0,3587)	2,2960** (0,0345)	0,1731	-0,0440 (0,3548)	2,3105** (0,0228)	0,2044
12	-0,0026 (0,9732)	2,6804* (0,0958)	0,0991	-0,0638 (0,1870)	2,4865** (0,0146)	0,2491	-0,0587 (0,1958)	2,4718** (0,0105)	0,2737

Table 12.2

k=30

t	Type 1 alpha	Type 1 non-lottery portfolio return	Type 1 adj. Rsquared	Type 2 alpha	Type 2 non-lottery portfolio return	Type 2 adj. Rsquared	Type 3 alpha	Type 3 non-lottery portfolio return	Type 3 adj. Rsquared
1	0,0043 (0,3375)	0,9334*** (4,9228)	0,4365	0,0004 (0,0413)	0,9994*** (7,2844)	0,6344	-0,0021 (-0,1676)	0,7652*** (4,0290)	0,3368
2	0,0115 (0,5969)	1,4905*** (0,0001)	0,4195	-0,0023 (0,8720)	1,5500*** (0,0000)	0,6550	0,0026 (0,9032)	1,2507*** (0,0003)	0,3520
3	0,0100 (0,7426)	1,4958*** (0,0020)	0,2768	-0,0119 (0,5649)	1,6633*** (0,0000)	0,5188	-0,0003 (0,9909)	1,2805*** (0,0027)	0,2614
4	0,0042 (0,9048)	1,6701*** (0,0037)	0,2531	-0,0215 (0,4217)	1,7871*** (0,0002)	0,4083	0,0017 (0,9601)	1,4084*** (0,0094)	0,2026
5	-0,0135 (0,7469)	1,3843* (0,0805)	0,0819	-0,0266 (0,4506)	1,7989*** (0,0095)	0,2098	-0,0003 (0,9935)	1,2676* (0,0858)	0,0780
6	-0,0248 (0,6262)	1,2401 (0,2347)	0,0191	-0,0325 (0,4469)	2,1180** (0,0216)	0,1676	-0,0025 (0,9567)	1,1588 (0,2274)	0,0209
7	-0,0415 (0,4851)	1,1414 (0,3371)	-0,0016	-0,0382 (0,4543)	1,8325* (0,0828)	0,0870	-0,0070 (0,8984)	1,1457 (0,3002)	0,0051
8	-0,0628 (0,3551)	0,9744 (0,4690)	-0,0203	-0,0518 (0,3804)	1,7436 (0,1490)	0,0510	-0,0227 (0,7137)	1,0781 (0,3853)	-0,0095
9	-0,0799 (0,3033)	0,4108 (0,7910)	-0,0440	-0,0728 (0,2740)	1,1619 (0,3906)	-0,0106	-0,0303 (0,6682)	0,4390 (0,7595)	-0,0428
10	-0,0875 (0,2648)	1,5720 (0,3209)	0,0017	-0,0736 (0,2821)	2,0163 (0,1561)	0,0528	-0,0418 (0,5530)	1,5990 (0,2696)	0,0136
11	-0,0978 (0,2340)	2,0022 (0,2242)	0,0281	-0,0755 (0,2764)	2,6487* (0,0691)	0,1194	-0,0483 (0,5092)	2,1044 (0,1610)	0,0534
12	-0,1239 (0,1673)	2,0878 (0,2339)	0,0265	-0,0995 (0,1634)	2,8675* (0,0516)	0,1498	-0,0777 (0,3352)	2,3823 (0,1424)	0,0665

t	Type 4 alpha	Type 4 non-lottery portfolio return	Type 4 adj. Rsquared	Type 5 alpha	Type 5 non-lottery portfolio return	Type 5 adj. Rsquared	Type 6 alpha	Type 6 non-lottery portfolio return	Type 6 adj. Rsquared
1	0,0029 (0,2886)	0,6501*** (4,3689)	0,3761	0,0017 (0,2414)	0,8211*** (7,7112)	0,6609	0,0088 (0,9502)	0,8606*** (6,2689)	0,5608
2	0,0106 (0,5380)	1,2482*** (0,0000)	0,4511	-0,0024 (0,8566)	1,3916*** (0,0000)	0,6338	0,0054 (0,7189)	1,3859*** (0,0000)	0,5732
3	-0,0026 (0,9184)	1,2852*** (0,0018)	0,2829	-0,0073 (0,7122)	1,5421*** (0,0000)	0,5040	0,0042 (0,8567)	1,5307*** (0,0001)	0,4212
4	-0,0079 (0,7898)	1,5300*** (0,0020)	0,2858	-0,0023 (0,9299)	1,7312*** (0,0002)	0,4017	0,0058 (0,8346)	1,7243*** (0,0003)	0,3716
5	-0,0126 (0,7378)	1,8491** (0,0118)	0,1972	0,0070 (0,8340)	2,1975*** (0,0013)	0,3181	0,0158 (0,6378)	2,2849*** (0,0010)	0,3314
6	-0,0078 (0,8687)	2,1981** (0,0294)	0,1487	0,0188 (0,6516)	2,4026*** (0,0084)	0,2244	0,0195 (0,6389)	2,3833*** (0,0091)	0,2201
7	-0,0127 (0,8272)	2,2060* (0,0669)	0,1011	0,0244 (0,6092)	2,0977** (0,0365)	0,1407	0,0175 (0,7144)	2,0449** (0,0415)	0,1324
8	-0,0223 (0,7380)	2,1045 (0,1247)	0,0631	0,0230 (0,6707)	1,9140* (0,0872)	0,0875	0,0085 (0,8742)	1,9570* (0,0788)	0,0944
9	-0,0308 (0,6821)	1,3856 (0,3698)	-0,0073	0,0128 (0,8271)	1,3142 (0,2785)	0,0107	-0,0045 (0,9393)	1,4627 (0,2372)	0,0214
10	-0,0417 (0,5890)	2,0429 (0,1996)	0,0349	0,0050 (0,9321)	2,1273* (0,0843)	0,0987	-0,0098 (0,8690)	2,2690* (0,0736)	0,1089
11	-0,0431 (0,6016)	2,3372 (0,1662)	0,0509	0,0004 (0,9950)	2,4502** (0,0485)	0,1469	-0,0154 (0,8004)	2,5113* (0,0521)	0,1414
12	-0,0469 (0,6104)	2,3057 (0,2109)	0,0347	-0,0184 (0,7528)	2,6400** (0,0326)	0,1868	-0,0365 (0,5491)	2,6904** (0,0359)	0,1791