UNIVERSIDADE TÉCNICA DE LISBOA

INSTITUTO SUPERIOR DE ECONOMIA E GESTÃO

MASTERS IN FINANCE

"RISK PROFILING: PERCEPTION AND REALITY"

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Orientation: Professor João Luís Correia Duque

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Abstract

Retail banks classification of clients according to their risk profile has been a theme very much under discussion in the last few years. In this paper we aim to investigate, for the affluent and private banking client segment, if the perception that people have of their risk profile effectively corresponds to their real risk profile as given by a measure of historical volatility. In addition, we analyze, on the real portfolio of financial investments, the impact of each of the following factors in regard to people's attitude towards risk: age, gender, degree of education, financial situation and investment experience.

JEL Classification: D81
Keywords: Risk Profiling, Risk Perception, Risk Aversion

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Any mistakes or omissions are from the exclusive responsibility of the author.

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1. Introduction

During the last few years, the classification of clients according to their risk profiles has been a theme under intense discussion, especially among retail banks. The new Markets in Financial Instruments Directive (MiFID), approved on the 27th of April 2007 by the European Union Council of Ministers has brought an even bigger sense of urgency to this theme.

For the majority of the investment products sold in the retail banks branches, “suitability” and “appropriateness” tests are nowadays a legal imposition and no longer a value added service provided by a minority of the players in the market. In this context, it becomes clear that in order to determine if an investment product is “suitable” and/or “appropriate” to a client, it is necessary to determine with as much precision as possible, the risk profile of that client. This is not an easy task. On one hand, there is no consensus regarding the type of questionnaire that has to be carried over in order to determine the risk profile of the client and, on the other hand, there is no empirical evidence that clients perception of their real risk profile is accurate or they actually think one way and, when facing a real investment decision, act in a different manner.

In this study, we examine, for the affluent and private banking segments of retail clients i) the relationship between the perceived volatility of a portfolio against the real volatility of the portfolio, and ii) the relationship between the real volatility of a portfolio with age, gender, degree of education, financial situation and investment experience. While studying these relationships, we will enter into the concepts of behavioural finance, as some of the conclusions simply cannot be explained consistently by traditional finance standards.

The first questions that we have to ask ourselves are ... How do we think? Are we rational? These are not easy questions but will have a lot to do with the purpose of this study. Fama (1970) studied the efficiency of the markets, arguing that prices reflect all the public information available and that abnormal returns cannot last for long as arbitrage rapidly induces quick adjustments. Basically, whenever there is new public information available, once the information is processed, investors will act, buying or selling in the market. In this case, the asset prices would, on average, reflect its real/true value. However, the truth is that we can question market efficiency. Empirical data can be inconsistent with the efficiency premise. Deviations between the fundamental value and the market prices do exist and, sometimes last for long periods of time.

Traditional finance presupposes that economic agents are rational. Van Neumann and Morgenstern (1947) stated that people use the expected utility theory in their decision making process and that all new information is interpreted correctly and that probabilities are constantly updated. Also, this principle of perfect rationality is the starting point of current financial theory (CAPM, Black & Scholes, Modern Portfolio Management, etc.). On all of these studies, objectivity and precision are rules and, without exception, the focus is put either in prices, volumes, dividends, results, etc. (market variables) but no interest is put on the agents themselves, people who produce these data (traders, portfolio managers, etc.). But these agents are humans and the human mind is more complex than any of the models referred. This is where behavioural finance takes importance, introducing new theories about the human behaviour.

Ritter (2003) provided a very useful introduction to behavioural finance, pointing out that its two main blocks are cognitive psychology (the way people think) and the limits to arbitrage (when are arbitrage forces not effective).

- On the cognitive psychology, some of the interesting patterns found were: i) Heuristics: People like rules of thumb (simple rules to be used on the decision process) because people have time and cognitive capacity limitations, and so, systematic biases occur. Most of the times, for example, when having *N* choices to invest money, people tend to allocate *1/N* of the available funds to each of the options; ii) Overconfidence (also known as self-deception theory): People tend to be overconfident about their abilities; iii) Mental Accounting: People tend to separate decision that should be made together; iv) Representativeness: People tend to underweight long term averages, putting too much weight on recent experiences; and v) Disposition Effect: This refers to the fact that people tend to avoid realizing losses and seek to realize gains;
- On the limits to arbitrage, two points were distinguished: i) Misvaluations that are recurrent or arbitrageable; and ii) those who are non-repeating and long term in nature.

Barberis & Thaler (2003) also applied the behavioural finance approach on the limits to arbitrage as well as for psychological factor. On limits to arbitrage, they used analysis of a Ford and General Motors example to justify limits to arbitrage and its risks and costs. They used another example with the analysis of Royal Dutch and Shell Transport double quoting on the stock exchange (USA and in the UK) to provide more evidence of this matter. On psychology, they referred to the Prospect theory.

The Prospect Theory is maybe the most promising for financial applications. It is the most successful at capturing experimental results. It simply tries to capture people's attitudes to risky gambles as parsimoniously as possible. Kahneman and Tversky (1979) lay out the original version of the Prospect Theory, designed for gambles with most two non-zero outcomes and reach the conclusion that: i) when choosing between different gambles, people pick the one with the highest value; ii) people are risk averse over gains and risk seeking over losses; iii) people are more sensitive to probabilities at higher probability levels.

Shiller (2000) focused his attention on factors that, in his opinion affect the behaviour of investors in a way that influences their investment decisions and their judgement to the equity market valuations. In his study, he divides his approach towards the factors that influence the stock market valuations and investor investment decisions in three building blocks: structural factors, cultural factors and psychological factors. This approach was not quantitative as it focused solely on the equity market and not on a diversified portfolio, but opened the door to a wider discussion about the irrational exuberance of investors and its effects on investment decisions.

- On the structural factors, several are mentioned as having a relevant impact towards what is called "Irrational Exuberance": i) the arrival of internet in a strong economic environment is one of the factors mentioned. The internet boom of the 90's made everybody aware of the strong technological change taking place at the time. However, it was not until the late 90's when everybody was aware of this reality. In Shiller's opinion, the internet success cannot be separated from the Nasdaq performance at that time; ii) the economic performance gap between the United States and the rest of the world associated with the fall of its economic rivals is another factor that contributed to an important confidence boost that lead to "Irrational Exuberance"; iii) the fact that the so called baby boomers are now between 45 and 65 years old is another important factor because this generation, being born in a time of clear prosperity, is one of the biggest investors in the stock market, contributing to its multiple expansion in the 90's; iv) the big development of the media and the appearance of market 100% dedicated channels was another very important factor that led to "Irrational Exuberance". People had more and more information available and the media had more and more enhanced money sections on newspapers, magazines and television, boosting stock market awareness and consequently demand for stocks; v) the increasingly optimistic analyst forecasts also led to the favourable sentiment for the stock market; vi) the expansion of defined contribution pension plans, which heavily invested in equities also increased the demand for stocks, indirectly increasing “Irrational Exuberance”; vii) the expansion of mutual funds had a similar effect to the one of the of defined contribution pension plans and viii) the development of discount brokers, day traders and other market associated services diminished the cost of stock market investing, contributing as a confidence boost in stock market investing.

- On the cultural factors, the focus is put on the impact of the media in the cultural change. The competition for the hot news stories, the promotion of debate, the delivery of the market outlook, the big news and the tag along news of the following days and the intense coverage of each and every important event lead to a different way of thinking, to a different knowledge of the market and to a new way of investing.
- On the psychological factors, the discussion is centred on the quantitative anchors and the moral anchors of the market, the investor overconfidence and intuitive judgement that affect investment decisions.

In general, all these factors affect the way people invest in the equity markets. One good question is if they do affect their perceived risk profile? And their real risk profile?

Glaeser & Weber (2007) discussed situationalism and economics. The thread that runs much behavioural economics is that individuals often do a bad job maximizing their long-run welfare. They state that some papers show that suboptimal behaviour stems from limited powers of reasoning. Others show that extreme orientation towards the present causes people to neglect future well-being. Others argue that decisions are so context dependent that we should treat preferences as either highly unstable or essentially nonexistent. Does this mean that people are more risk averse in a bear market and less risk averse on a bull market (real risk profile movement)? Does people’s perceived risk profile change with economic cycles?

Van der Sar (2004) reviewed the state of various aspects of behavioural finance. Their main conclusions were that behavioural finance represents an alternative way of looking at financial markets, characterized by what may be called a new null hypothesis that accommodates deviating behaviour. Having this in mind, the manner of conducting research differs from the standard finance approach on several dimensions:

- Most behavioural studies have an empirical component in common, put an emphasis on the descriptive value and claim no normative significance;
- Behavioural choice models often show a high predictive value, but criticism is that they usually lack robustness;
- It is not uncommon that the method is inductive in a certain manner. Observed regularities in anomalous behaviour at an individual level of financial decision making are typically used to construct a behavioural model for a higher aggregate. This contrasts with the standard finance approach which aims to derive theorems with a broad reach and usually start from a specific set of assumptions;
- A central position is taken by financial decision making as well as financial markets, whereas the standard finance approach is greatly concerned with the development of equilibrium theories and the pricing of risk, that is, the market;
- The focus is not only on the outcomes but also on the generating process. Theoretical as well as empirical results from other behavioural sciences, such as psychology and decision theories that are more process oriented, may therefore be of use and consistency should be focused on.

Having the above factors in mind, can we study people's risk profile using the prerogatives of traditional finance, ignoring these behavioural factors, like the MiFID's requirements in a sort of know your client initiative leads financial institution to do?

Focusing on the true purpose of this study, we intend to examine in detail, for the affluent and private banking client segment, not only the relationship between what individuals perceive to be their risk profile and their real risk profile but also the impact of a variety of factors (age, gender, degree of education, financial situation and investment experience) on their real portfolios. The present study uses a database of 86 risk profile questionnaires from private individuals, selected randomly from a local Portuguese bank client base, in the referred client segment, together with respective 86 real monthly statements. This data provides a unique opportunity to the kind of analysis proposed on this study.

We have not really seen any study that would start from people's statements (maybe due to unavailability of data), which means real data of volatility, and then try to capture the deviations to perceived volatility. However, regarding the second purpose of this study which focuses on the effect of several factors on real volatility, Bellante and Green (2004) have done a very interesting previous approach. They studied the impact on risk aversion of factors like age, race, gender, education, health status and the number of children. More specifically it has the objective to examine the effect of each of these factors on relative risk aversion, i.e., the effect of each of these factors on the tendency of individuals to increase (decrease) the fraction of their wealth in risky assets as that wealth increases. Using previous research by Morin and Suarez (1983) and Bellante and Saba (1986), which used an earlier formulation by Friend and Blume (1975) to build their empirical models on relative risk aversion, their approach found clear support for the postulate of decreasing relative risk aversion among the elderly. However, it was also found that relative risk aversion increases modestly as the elderly grow older. In contrast to previous studies, these two finding are not sensitive to changes in the treatment of housing. The personal characteristics of race, education, health status and the number of children significantly affected the portfolio allocation. However, the directions of these effects were in fact sensitive to the treatment of housing. It is argued that, particularly among the elderly, housing should be treated as a riskless asset and it is probably regarded as that by the elderly themselves. It was found that the sign of the referred variables conform to priori expectations when housing was considered a riskless asset, but otherwise did not conform.

Also, Christiansen et al (2004) analysed the impact of education in holding stocks, in a study where they tested the hypothesis that economists hold stocks more than other people due to informational advantages and argued that indeed, there was a higher probability of economists holding equity than on any other education. They concluded that it is confirmed that economists are more prone to hold stocks. The result is clear, as an individual with formal education in economics shows a much higher probability of participating in the stock market than an individual with 9 years of basic education. Their paper shows that an important asset in the wealth portfolio (in terms of value), namely human capital, is also an important determinant of individuals choice of investment in other risky assets. Therefore, future theoretical models of portfolio choice and capital asset pricing should include the role of human capital (Palacios-Huerta (2003) and Constantinides and Duffie (1996)).

Let’s see how build on these ideas to answer our main question marks.

2. Data

For the present study we used two sources of data from a Portuguese domiciled financial institution, operating in the affluent and private banking retail market.

Just to clarify the target client base of this study, this financial institution defines an affluent client when it has a potential involvement of more than € 50.000,00 in investable assets and a private banking client when it has a potential involvement of more than € 250.000,00 in investable assets with the financial institution in question.

2.1 Questionnaires

We started our study by taking a look on some industry comparable questionnaires to check if there were some big differences between our sample and others used by some competitors.

As we referred on our introductory note, there is no consensus regarding the type of questionnaire that has to be carried over in order to determine the risk profile of the client which means that when you start doing some research on this matter, you get to very different propositions. Matching investors risk profile with the appropriate investment has always been the cornerstone of the investment advisory process – this is what, in our opinion, we have to keep in mind when analysing different types of questionnaires. No matter how different they look, if they have 10, 13, or 20 questions, how specific they are, etc., what is really important are the structural themes they want to see answered. What we mean by that is: What is the objective of making such a questionnaire? And here, we believe there is a common path that arose from the issues raised by the Markets in Financial Instruments Directive (MiFID) legislation. Markets in Financial Instruments Directive (MiFID) is by no means accepted as the answer to provide "appropriate" and "suitable" products to investors but is a good step in that direction and was at least able to generate a sort of a common ground for financial institutions to start from.

However, there is an increasing amount of discussion going on about several factors that might influence one's risk profile. Usually, independent of shapes and sizes, questionnaires tend to have as rationale for calculating one's risk profile, the buffer that one has to absorb losses. The bigger the buffer the higher the risk one can take, the lower the buffer the lower the risk one can take. If you are young, have no health problems, make good money and have few dependents, then you can make up for any losses in years to come. However if you are older, ill and dependent on the income from your investments to cover your dependents living costs, then you cannot make any mistakes. The factors mentioned are just a few and one can allocate different degrees of importance to each of them. In the end, one figured out a scoring system, you get the result. But how accurate is this result?

This is a difficult question. Generally speaking, the rationale behind these methods is good but far from optimal. Factors such as experience, knowledge are not easy to read or to score. Factor like net wealth (and how you measure it?) and its impact (how important it is?) in one's risk profile is also not easy to score.

In the end, you really have to put numbers into things and get to a scoring model that gives your a risk profile for a certain client. All these factors can be a good topic for intense discussions and include a great degree of intangibility but that doesn't mean we should dispense with risk profilers altogether. Their intent is good and they are certainly better than no screening at all. But in many instances they are too general and, as a result, certain clients can fall right through the cracks.

One other topic that has been in everybody's mind lately is how the profiles change over time. On top of that you can question that even if one's profile has not changed, one profile towards a specific investment has change. Take for example an investment with three months left to run versus one with seven years left to run. One's risk profile may not have changed, but any adviser worth their money will tell you that the investment with three months left to run needs to be protected against short-term volatility.

The bottom line is that no standard risk selection process can offer the perfect solution. Not all clients slot neatly into pre-defined "one-size-fits-all" categories. Nothing can replace getting to know a client individually - and invariably the best way to achieve this is for the client and adviser to spend time together. Ultimately this is very good news for financial advisers, as they are not likely to be replaced with on-line computerized risk profilers, no matter how sophisticated these become.

In this study we analysed 5 different questionnaires from different financial institutions/advisers. To be more specific, we took a questionnaire from Barclays Wealth in the UK, from Citibank in Belgium, from Finametrica in Italy, from ABN Amro in the Netherlands (4 big financial institutions) and finally, one from Financial Innovations in the UK (a well known financial adviser). We did not have access to the scoring breakdown because we're talking about proprietary models but, all the themes are pretty much the same and all factors are in line between one and other and also in line with the questionnaire used for the purpose of this study (we attach as Appendix of the questionnaire used for this study and also as an example, the questionnaire used by Citigroup Belgium). In our opinion, despite having very different layouts and questions, typically, it's just different ways of approaching the same theme and to get answers to the same central objectives.

Focusing on our study, we took 86 risk profile questionnaires, used by the financial institution in question to determine the risk profile of their clients. The questionnaires included 62 men and 24 women, with an average age of around 55.6 years. The youngest individual was 20 years old and the oldest was 86 years old.

Below we can see a brief description of the gender distribution by age brackets:

Age Brackets	***Clients***	***% of Clients***
> 65	20	23.26%
> 45 and $\leq$ 65	45	52.33%
$\leq$ 45	21	24.42%
Total	**86**	**100.00%**

Age Brackets	***Men***	***% of Men***	***Women***	***% of Women***
> 65	18	29.03%	2	8.33%
> 45 and $\leq$ 65	32	51.61%	13	54.17%
$\leq$ 45	12	19.35%	9	37.50%
Total	**62**	**100.00%**	**24**	**100.00%**

More than 50% of the clients are between 45 and 65 years old. There are no big differences from the total numbers when we look at the gender and, as far as the financial institution in question is concerned, we were told that this is pretty much in line with the distribution of their whole client base.

In our approach, we really do not intend to question the construction of the questionnaire, its scoring or even the way that this financial institution classifies each client in a specific profile. This is something that is, in reality, being used, and so, it constitutes a good example of how financial institutions are dealing with the new requirements of the new Markets in Financial Instruments

Directive (MiFID), approved on the 27th of April 2007 by the European Union Council of Ministers, and how “appropriateness” and “suitability” tests are being applied to products/clients.

The questionnaire is divided in three modules. The first module relates to Knowledge and Experience information and is constituted by 5 questions. The second module relates to Financial Situation and is constituted by 4 questions. Finally, the third and last module relates to Investment Objectives and is constituted by 4 questions. For detailed information about the questionnaire, please refer to Appendix 1.

Computing the scoring of the questionnaire, the result will be the classification of each client under 1 out of 5 profiles. Each of these profiles has a volatility range associated with it. The volatility ranges were decided by the financial institution in question. When the clients sign the results of the questionnaire, they accept the respective volatility range. If the client does not agree with the volatility range given by the questionnaire, its only option is to reconsider one or more of his answers. Accepting the results means accepting a risk profile.

Profile	***Name of Profile***	***Volatility Range***
Profile 1	Very Conservative	< 3%
Profile 2	Conservative	[3% - 7%[
Profile 3	Moderate	[7% - 12%[
Profile 4	Dynamic	[12% - 17%[
Profile 5	Aggressive	>= 17%

As the name itself indicates, the Profile 1 – Very Conservative - is the most defensive risk profile or the more risk averse and, the Profile 5 – Aggressive - is the most aggressive profile or the less risk averse.

Just as a note, all the products in the financial institution in question are pre-qualified according to this risk profiles so, in principle, before acquiring any product, clients are aware if it is or it is not in agreement with their profile. Of course, what matters is that their portfolio in aggregate complies with the risk profiles accepted when signing the questionnaire.

One other point to have in mind is that from answering the questionnaire, the classification in terms of risk profile is valid only for the financial institution in question and that the answers to the questionnaire questions should be addressed as so. The financial institution in question addresses that it does not have means to assert the shape of risk appetite of its clients with other financial institutions and so, it assumes that the questions are referred only to this specific relationship. It claims that if treated otherwise, the process of attributing a risk profile to a client and keep it up to date would be very time consuming, would involve a lot of accessory work and consequently, would be very difficult to manage.

2.2 Integrated Statements

The second source of data was a group of 86 integrated monthly statements from the same clients for which we had the filled questionnaires. We took the last available statements, relating to the period where the questionnaire was filled (between June and July 2008).

To conclude on the target client base, at the assets under analysis level, the average of 86 observations was of € 403,260.81. The minimum amount observed on a statement was € 186.65 and the maximum amount observed was € 4,995,724.45 (these amounts are net of the adjustments referred below).

Amount Brackets	***Amount (€)***	***% of Amount***	***Clients***	***% of Clients***
>1.000.000	14,792,888.32	42.65%	6	6.98%
> 500.000 and ≤ 1.000.000	8,694,299.46	25.07%	12	13.95%
> 250.000 and ≤ 500.000	6,778,334.65	19.55%	20	23.26%
< 250.000	4,414,906.94	12.73%	48	55.81%
Total	**34,680,429.37**	**100.00%**	**86**	**100.00%**

As we can see from the table above, 6.98% of the clients represent around 42.65% of the assets under management that we're studying, which means there is a big concentration of money in a small portion of our sample. On the other hand, 55.81% of the clients represent only 12.73% of the assets under management in question. These numbers do not say much and have no significance to our study because we're not focusing on weighted portfolio figures but on each portfolio individually.

We made an extensive analysis of the statements, making some adjustments to make it more appropriate for the purpose of this study. In terms of the assets under analysis, we did not take into account the sight deposits account balance because we do not consider it an asset. In terms of analysis of the assets, in order to calculate the volatility of the portfolios, we took the three year volatility with monthly price observations for every asset. For time deposits, we assumed zero volatility. When historical data was missing, which happened in just a few cases in equities, we assumed the missing observations as the average of the existing observations, which leads to slightly lower volatility on those cases. However, this effect is almost negligible overall.

For the purpose of the calculation of the volatility of the portfolios, we used 36 monthly price observations. The decision to use monthly observations arose from the fact that a good number of the assets on the clients' statements did not produce more regular prices/valuations.

Taking into account all this data, we get all the information we need to i) compare the perceived (accepted) volatility by the client when signing the results of the questionnaire with the real volatility taken from the statement analysis and ii) examine the relationship between the real volatility taken from the statement analysis and 5 different variables: age, gender, degree of education, financial situation and investment experience.

3. Method & Results

3.1 Variables Definition

The variables used in this study cover 3 areas: real volatility, the answers to the questionnaires and perceived volatility. Also, from the answers to the questionnaires, we take two other characteristics that we include on the study, which are gender and age.

We ended up using 57 variables in total.

3.1.1 The Volatility

As we briefly referred on section 2.2, for the purpose of calculating the volatility of the clients' portfolios, we used 36 monthly price observations.

Working on the data, we calculated the logarithms of the price change for each asset for the three years of observations. We then multiplied each monthly return by the percentage that each asset represented in the balance of the portfolio and summed the results for each month for all the assets. We end up with 35 observations for each portfolio. We proceeded by doing the standard deviation of these observations and multiplying it by the square root of 12 to get an annualized number and end up to the real volatility of the portfolio.

Doing this exercise, we started questioning the quality of the data because of the specific period in question. Our first numbers are from the 31st of of July 2005 and our final numbers are from the 30th of June 2008. Most global stock markets made their all time highs in 2007 or 2008. From that peak many of them fell hard to reach their troughs in early 2009 and that might have had some influence on the volatility of the client's portfolios. Although our data misses out on a big chunk of 2008's events, it already incorporates some very bad news.

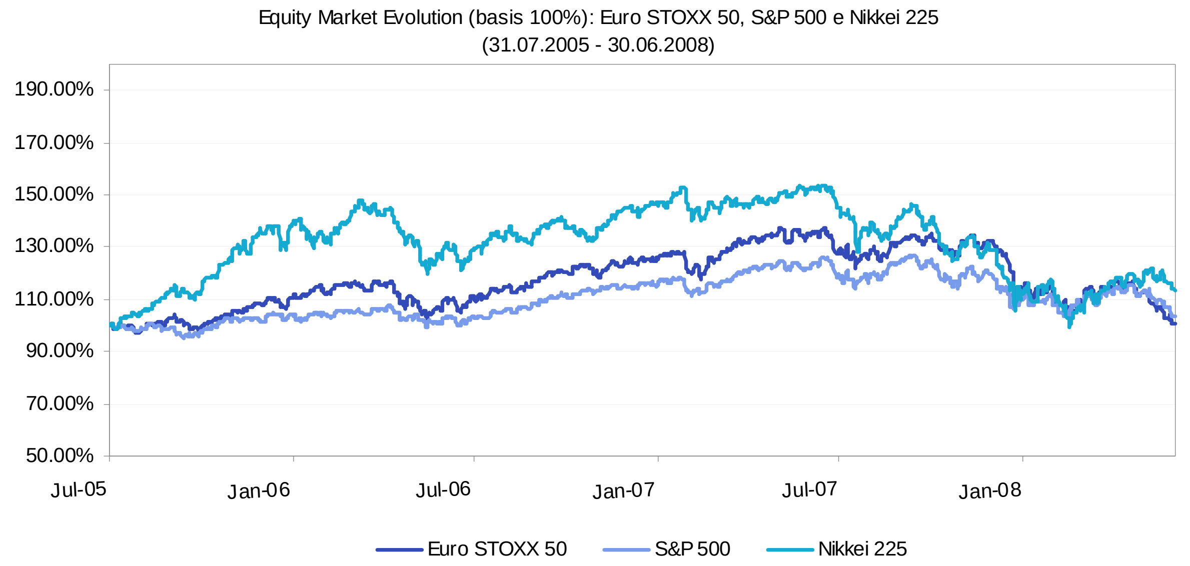
The credit markets problems had long started. Since 2007, US housing prices had started to fall, especially on the so called subprime market. Homeowners were finding themselves with underwater loans (they owed lenders more than the home was worth). As mortgage defaults started to rise, the US started to falter and fear crept into the credit markets. Despite the efforts of the Federal Reserve, the destabilization of the credit market quickly spread to the national financial system and, consequently, to the US equity markets and world equity markets.

The first big victim was discovered on March 13, 2008. On that date, Bear Stearns advised the Federal Reserve that its liquidity position had deteriorated and that it would file for bankruptcy unless alternative sources of funds were made available. Two days later, Bear Stearns agreed to merge with JP Morgan Chase in a deal that wiped out 90% of Bear Stearns' market value.

So, by mid 2008, bells were ringing all around the world. Investors were facing interest rate cuts to stimulate economy, equity markets were falling, credit markets were frozen, and confidence was dropping in both consumer and corporate levels. On top of that, the news on the press were all but positive.

To illustrate, we take a look at some numbers on equity indices from G3 economies for the period in study.

Graph with the 3y Data (DJ Euro STOXX, S&P 500 and Nikkei 225)



Index	***Peak Level***	***Peak Date***	***End 2007 Level 31.12.2007***	***% From Peak***	***Mid 2008 Level 30.06.2008***	***% From Peak***
DJ Euro STOXX 50	4,557.57	16.07.2007	4,399.72	-3.47%	3,352.81	-26.43%
S&P 500	1,565.15	09.10.2007	1,468.36	-6.18%	1,280.00	-18.22%
Nikkei 225	18,261.98	09.07.2007	15,307.78	-16.18%	13,481.38	-26.18%

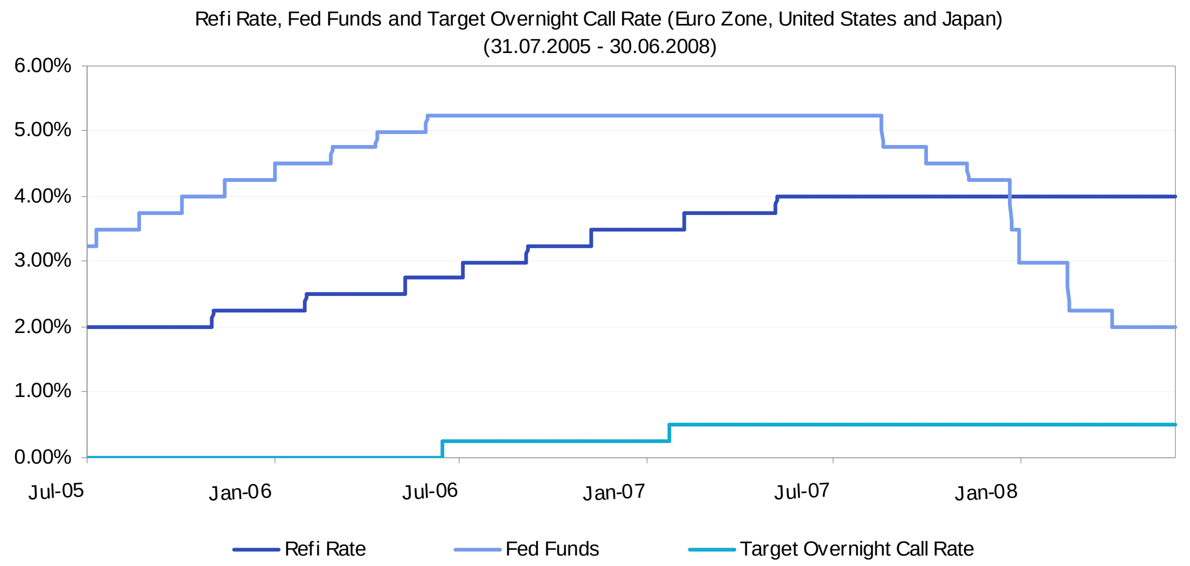
Index	*Bottom Level*	*Bottom Date*	*End 2007 Level 31.12.2007*	*% From Bottom*	*Mid 2008 Level 30.06.2008*	*% From Bottom*
DJ Euro STOXX 50	3,224.10	26.08.2005	4,399.72	+36.46%	3,352.81	+3.99%
S&P 500	1,176.84	13.10.2005	1,468.36	+24.77%	1,280.00	+8.77%
Nikkei 225	11,766.48	05.08.2005	15,307.78	+30.10%	13,481.38	+14.57%

We can see that at the end of 2007, for the period in study (31.07.2005 – 30.06.2008), taking the DJ Euro STOXX 50 as an example, the market was up 36.46% from it's bottom but, by mid 2008, the market was up just 3.99% from bottom. For the same index, by the end of 2007, the market was just 3.47% from peak but, by mid 2008, the market was already 26.46% down from its peak. These differences refer only to the evolution of the Euro Zone equity market in 6 months. This represents a huge movement in such a short period, which could well have influenced real volatility data in clients' portfolios, even without any client driven change on its assets.

This evolution is similar in all G3 regions, despite having a lower absolute impact in the United States and in Japan.

In terms of the interest rate cycle, we can take a look at the data for the same time frame to further illustrate this thoughts.

Graph with the 3y Data (Refi Rate, Fed Funds and Target Overnight Call Rate)



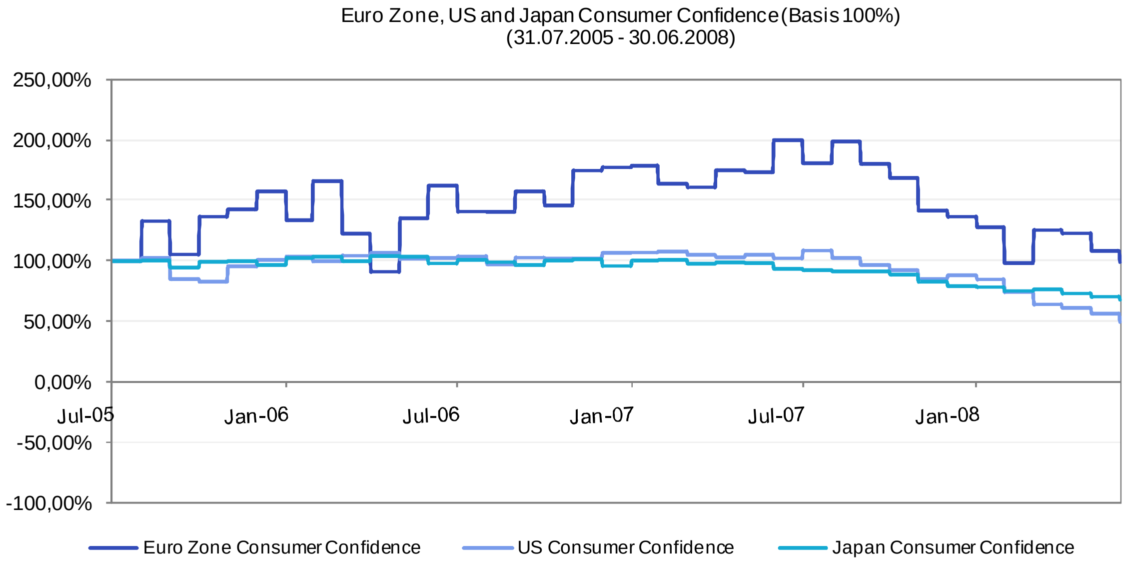
Rate	***Peak Level***	***Peak Date***	***End 2007 Level 31.12.2007***	***Difference From Peak***	***Mid 2008 Level 30.06.2008***	***Difference From Peak***
Refi Rate	4.00%	06.06.2007 – 30.06.2008	4.00%	0.00%	4.00%	0.00%
Fed Funds	5.25%	29.06.2006 – 18.09.2007	4.25%	-1.00%	2.00%	-3.25%
Target O/N Call Rate	0.50%	22.02.2007 – 30.06.2008	0.50%	0.00%	0.50%	0.00%

Index	***Bottom Level***	***Bottom Date***	***End 2007 Level 31.12.2007***	***Difference From Bottom***	***Mid 2008 Level 30.06.2008***	***Difference From Bottom***
Refi Rate	2.00%	31.07.2005 – 30.11.2005	4.00%	+2.00%	+4.00%	+2.00%
Fed Funds	2.00%	30.04.2008 – 30.06.2008	4.25%	+2.25%	+2.00%	+2.00%
Target O/N Call Rate	0.00%	09.03.2006 – 13.07.2006	0.50%	+0.50%	+0.50%	+0.50%

The reality here is a bit different from the one seen for the equity markets. In this case, Euro Zone and Japan had not started the easing bias at the end date of our analysis (30.06.2008). In the United States, the example is different. The Fed started cutting interest rates sooner than Euro Zone or Japan and, by the 30th of June 2008, had already cut the Fed Funds interest rate by 3.25%, coming down to 2% from a peak 5.25% (at the end of 2007, it had only cut rates by 1.00%). On a bottom to current level analysis, there is nothing special to comment as the only change occurred in Japan with a move from 0.00% to 0.50%.

Finally, on the confidence numbers, we can also observe some deep movements, showing that the evolution of the other indicators was taking its toe on the confidence side.

Graph with the 3y Data (Euro Zone Consumer Confidence, United States Consumer Confidence and Japan Consumer Confidence)



Confidence Index	***Peak Level***	***Peak Date***	***End 2007 Level 31.12.2007***	***Difference From Peak***	***Mid 2008 Level 30.06.2008***	***Difference From Peak***
Euro Zone Consumer Confidence	20.43	30.06.2007	14.00	-31.47%	10.18	-50.17%
US Consumer Confidence	111.90	31.07.2007	90.60	-19.03%	51.00	-54.42
Japan Consumer Confidence	50.20	30.04.2006	38.30	-23.71%	32.90	-34.46%

Confidence Index	***Bottom Level***	***Bottom Date***	***End 2007 Level 31.12.2007***	***Difference From Bottom***	***Mid 2008 Level 30.06.2008***	***Difference From Bottom***
Euro Zone Consumer Confidence	9.38	30.04.2006	14.00	+49.25%	10.18	+8.53%
US Consumer Confidence	51.00	30.06.2008	90.60	+77.65%	51.00	0.00%
Japan Consumer Confidence	32.90	30.06.2008	38.30	+16.41%	32.90	0.00%

We can observe that from peak levels, there is a clear negative tendency in all regions, with consumer confidence levels falling progressively since mid 2007 for Euro Zone and United States and since April 2006 for Japan. On top of that, we can see that from bottom levels, consumer confidence shows no recovery at the end date of our analysis, meaning that it is possible that the last 6 months of our data might have been influenced also from this factor.

Having this in mind, we decided that we should also study the volatility of the clients' portfolios taking out the last 6 months of data. The objective was to reduce the bias effect of the market events we just mentioned on the clients portfolio volatility.

By doing this, we ended up studying volatility in two time frames. One based on 36 price observations and 35 monthly return observations (REALVOL35) and another on with 30 price observations and 29 monthly return observations (REALVOL29). In most of the cases, we ended up working the the logarithms of the real volatility data (LREALVOL35 and LREALVOL29).

3.1.2 The Questionnaire and Perceived Volatility

As referred on section 2.1, questionnaire is divided in three modules and has a total of 13 questions. Computing the scoring of the questionnaire, the result will be the classification of each client under 1 out of 5 profiles, each with and associated a volatility range, which is accepted by the clients when they sign the results of the questionnaires. This means that, in fact, clients accept a risk profile and the volatility interval linked to it or, in other words, they state their perceived volatility.

For the treatment of the risk profiles and perceived volatility, we used:

- PROFILEi, where i=1,2,3,4 are dummy variables which take the value 1 when it refers to the profile of the client given by the questionnaire and zero otherwise.
- PROFILEVOL represents the client's perceived volatility. As referred before, after computing the scoring of the questionnaire, the result will be the classification of each client under 1 out of 5 profiles. Each of these profiles has a volatility range associated with it and accepting the results means accepting a risk profile. In order to convert the range to a variable that could be worked with the ordinary least squares model, we did as follows for the five ranges:

Volatility Range	***Below Limit***	***Top Limit***	***PROFILEVOL***
< 3%	0%	3%	[(0% + 3%) / 2] = 1.5%

[3% - 7%[	3%	7%	[(3% + 7%) / 2] = 5.0%
[7% - 12%[	7%	12%	[(7% + 12%) / 2] = 9.5%
[12% - 17%[	12%	17%	[(12% + 17%) / 2] = 14.5%
>= 17%	17%	22%	[(17% + 22%*) / 2] = 19.5%

* we used 22% as a representation of the top of the range on Profile 5 because it is the maximum volatility that the financial institution in question considers adequate for this target client base in its advisory business.

For the treatment of the answers to the 13 questions on the questionnaires, we used the following variables:

- Q1Ai, where i = 1,2,3,4,5,6 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q2Ai, where i = 1,2,3,4 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q3Ai, where i = 1,2,4 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q4Ai, where i = 1,2,3 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q5Ai, where i = 1 is a dummy variable which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q6Ai, where i = 1,2,3 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q7Ai, where i = 1,2 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q8Ai, where i = 1,2,3,4 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q9Ai, where i = 1,2 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q10Ai, where i = 1,2,3,4 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.

- Q11Ai, where i = 1,2,3,4,5 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q12Ai, where i = 1,2,3,4,5 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.
- Q13Ai, where i = 1,2,3,4,5 are dummy variables which take the value of 1 when it refers to the answer picked by the investor on the questionnaire and zero otherwise.

3.1.3 Other Variables

Age and gender are variables present in a wide range of studies concerning risk profiles. As they are easy to infer from the questionnaire and, in order to study their relationship with real volatility, we decided to include, using the following variables:

- MALE represents a dummy variable with two possible outcomes, 1 if male, 0 if female.
- AGE represents the age of the investor.

3.2 Perceived Volatility versus Real Volatility

In order to compare the perceived (accepted) volatility by the client when signing the results of the questionnaire with the real volatility taken from the statement analysis, we started by calculating the average and the standard deviation of REALVOL35 figures per risk profile.

REALVOL35 Data

Profile	*N*	*Mean*	*Standard Deviation*
1	9	10.07%	13.13%
2	30	7.09%	5.41%
3	26	7.65%	5.45%
4	16	7.15%	3.92%
5	5	11.03%	11.33%
Total	86	7.81%	6.72%

The results were far from what one would expect. The average volatility per risk profile shows strange results when compared with the reference volatility ranges accepted by the clients when signing the questionnaires and, in some cases (especially in Profile 1), shows very high standard deviation figures. Profile 1 is completely out of the expected range, Profiles 2, 3 and 4 show similar results and, Profile 5 show a consistent and expected result, although below its reference range levels.

In addition, the relationship between the average volatilities per profile does not show any growth from Profile 1 up to Profile 5. Profile 1 is the second most volatile of the 5 profiles, just below Profile 5 and, Profile 2, Profile 3 and Profile 4 show very similar results. This is clearly not an expected result and, at first glance, demonstrates the existence of a big gap between perceived and real volatility.

In relation to the standard deviation figures, they follow the means, as expected.

The average volatility for the 86 portfolios, being around 7.8% is where one would expect it to be, showing that the average client is somewhere around Profile 2 and Profile 3, heading a bit more towards Profile 3.

In front of this figures, we questioned if the last 6 months of data concerning the real volatility figures represented by REALVOL35 could have had a determinant impact on unexpected proportion of these results.

In reality, the table below show very similar results for REALVOL29 when compared to REALVOL35.

REALVOL29 Data

Profile	***N***	***Mean***	***Standard Deviation***
1	9	8.93%	11.21%
2	30	6.46%	4.85%
3	26	6.71%	4.33%
4	16	6.74%	4.47%
5	5	9.73%	8.73%
Total	86	7.04%	5.78%

The one thing worth mentioning in this case is that, in general, volatility fell across all profiles. The pattern is the same but with lower volatility levels.

Another way of looking at this could be transforming the results of the questionnaires in dummy variables in order to determine if there was any significance on each of the profiles against REALVOL35 (and/or REALVOL29).

In this case, using real volatility as the dependent variable (REALVOL35), we tested it against intercept (C) and each of the profile results (we'll call this Equation 1):

Equation 1

$$REALVOL35 = \beta 1 + \beta 2\ PROFILE1 + \beta 3\ PROFILE2 + \beta 4\ PROFILE3 + \beta 5\ PROFILE4 + \upsilon$$

Dependent Variable: REALVOL35
Method: Least Squares
Date: 11/11/09 Time: 16:31
Sample: 1 86
Included observations: 86
White Heteroskedasticity-Consistent Standard Errors & Covariance

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.110265	0.046690	2.361662	0.0206
PROFILE1	-0.009517	0.063158	-0.150683	0.8806
PROFILE2	-0.039361	0.047750	-0.824325	0.4122
PROFILE3	-0.033811	0.047923	-0.705527	0.4825
PROFILE4	-0.038725	0.047703	-0.811782	0.4193

R-squared	0.031545	Mean dependent var	0.078112
Adjusted R-squared	-0.016280	S.D. dependent var	0.067182
S.E. of regression	0.067727	Akaike info criterion	-2.490291
Sum squared resid	0.371540	Schwarz criterion	-2.347596
Log likelihood	112.0825	Hannan-Quinn criter.	-2.432863
F-statistic	0.659588	Durbin-Watson stat	1.560487
Prob(F-statistic)	0.621859		

As we can see on this analysis, the PROFILE1, PROFILE2, PROFILE3 and PROFILE4 variables have no significance on the model, or in other words, it has no explicative power over the dependent variable.

Its p value is way too high which means we cannot reject the possibility of the coefficient being null.

Note that we used a robust estimation approach to estimate standard errors due to the fact that our model could suffer from heteroskedasticity, as we can see, using for instance, the Breuch-Pagan-Godfrey test.

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	2.246767	Prob. F(4,81)	0.0712
Obs*R-squared	8.588877	Prob. Chi-Square(4)	0.0722
Scaled explained SS	36.20743	Prob. Chi-Square(4)	0.0000

Testing residuals heteroskedasticity consistent standard errors & covariance with Breuch-Pagan-Godfrey, we conclude that p equals 0.0712. At this levels, it's on the limits of rejection.

Another way to correct heteroskedasticity, as it is well known, is to transform the dependent variable using logarithms. In this case, using the logarithm of real volatility as the dependent variable (LREALVOL35), we tested it against intercept (C) and each of the profile results (we'll call this Equation 2):

Equation 2

$$LREALVOL35 = \beta 1 + \beta 2\ PROFILE1 + \beta 3\ PROFILE2 + \beta 4\ PROFILE3 + \beta 5\ PROFILE4 + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:28
Sample: 1 86
Included observations: 85

	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.183354	0.372874	-5.855478	0.0000
PROFILE1	-0.681235	0.448139	-1.520144	0.1324
PROFILE2	-0.747847	0.396955	-1.883961	0.0632
PROFILE3	-0.548495	0.400531	-1.369420	0.1747
PROFILE4	-0.600157	0.416886	-1.439620	0.1539

R-squared	0.047120	Mean dependent var	-2.800177
Adjusted R-squared	-0.000524	S.D. dependent var	0.745552
S.E. of regression	0.745748	Akaike info criterion	2.308163
Sum squared resid	44.49116	Schwarz criterion	2.451849
Log likelihood	-93.09695	Hannan-Quinn criter.	2.365958
F-statistic	0.988992	Durbin-Watson stat	1.648742
Prob(F-statistic)	0.418456		

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.454866	Prob. F(4,80)	0.2238
Obs*R-squared	5.763895	Prob. Chi-Square(4)	0.2175
Scaled explained SS	9.045886	Prob. Chi-Square(4)	0.0600

Doing the regression with the logarithm of the real volatility figures, and then testing the residuals heteroskedasticity with Breuch-Pagan-Godfrey test we conclude that we've corrected heteroskedasticity (p-value equals 0.2238), and consequently there is no need to use the White consistent heteroskedasticity standard errors.

As we can see, the coefficients of the dummy variables are not statistically significant, (nor is the F-statistic), which confirm to the annoying conclusion that the logarithm of the real volatility (LRealVol35) and perceived volatility using the questionnaires seems to be unrelated. Using the LRealVol29 leads us to a similar conclusion. This is something that, at the beginning of our study, we didn't see coming. According to these findings, it is useless to make questionnaires of any kind to classify clients according to a risk profile based on their answers.

In front of all of these figures, we decided to analyze our sample to find a possible explanation for such results. Our main conclusion is that in each level of perceived volatility, mainly in Profile 1, there are a few very odd real volatility numbers. For instance, on Profile 1, the unexpected high volatility is due to two outliers, the most severe presenting the highest volatility in the whole sample (42.31% for REALVOL35 and 35.92% for REALVOL29), and the second outlier with a value of 18.30% for REALVOL35. We found similar, but less severe, situations for all the profile levels.

The study of these situations leads us to think that there is a small group of clients for which the risk profile questionnaire has no correspondence whatsoever to reality, while for other clients, the correspondence is more acceptable.

The next step was to define a criterion for acceptability and to discard the observations that did not follow this criterion.

The best solution was to change (widen) the volatility ranges by half of each of the downward and upward limits, using what below is described as the New Volatility Range and excluded from the regression the observations where REALVOL35 was situated outside these new ranges. For the purpose of the new regressions, we kept PROFILEVOL the same as before in order to keep the original reference intervals.

Old Volatility Range	***New Volatility Range***	***New Below Limit***	***New Top Limit***	***PROFILEVOL***
< 3%	< 4.5%	0%	4.5%	[(0% + 3%) / 2] = 1.5%
[3% - 7%[	[1.5% - 10.5%[	1.5%	10.5%	[(3% + 7%) / 2] = 5.0%
[7% - 12%[	[3.5% - 18.0%[	3.5%	18.0%	[(7% + 12%) / 2] = 9.5%
[12% - 17%[	[6% - 25.5%[	6.0%	25.5%	[(12% + 17%) / 2] = 14.5%
>= 17%	>= 17%	8.5%	33.0%	[(17% + 22%*) / 2] = 19.5%

* we used 22% as a representation of the top of the range on Profile 5 because it is the maximum volatility that the financial institution in question considers adequate for this target client base in its advisory business.

With this exercise, we shortened our sample from 86 observations to 62 observations. This new sample included 45 men and 18 women, with an average age of around 56.73 years. The youngest individual was 22 years old and the oldest was 85 years old.

Below we can see a brief description of the gender distribution by age brackets:

Age Brackets	***Clients***	***% of Clients***
> 65	15	24.19%
> 45 and $\leq$ 65	34	54.84%
$\leq$ 45	13	20.97%
Total	**62**	**100.00%**

Age Brackets	***Men***	***% of Men***	***Women***	***% of Women***
> 65	13	29.55%	2	11.11%
> 45 and $\leq$ 65	23	52.27%	11	61.11%

≤ 45	8	18.18%	5	27.78%
Total	**44**	**100.00%**	**18**	**100.00%**

Even after the adjustment, more than 50% of the clients in question are between 45 and 65 years old. There are still no big differences from the total numbers when we look at the gender and is still in line with the distribution of whole client base of the financial institution in question.

In terms of the statements analysis, with this reduced sample of 62 questionnaires, the average of the assets under went up to € 434,693.49 (+7.79% versus the 86 questionnaires sample). The minimum amount observed on a statement was € 1,829.17 and the maximum amount observed was € 4,995,724.45 (these amounts are net of the adjustments referred below).

Amount Brackets	***Amount (€)***	***% of Amount***	***Clients***	***% of Clients***
>1.000.000	11,759,076.32	43.63%	5	8.06%
> 500.000 and ≤ 1.000.000	7,089,282.73	26.30%	10	16.13%
> 250.000 and ≤ 500.000	4,893,529.17	18.16%	14	22.58%
< 250.000	3,209,107.90	11.91%	33	53.23%
Total	**26,950,996.12**	**100.00%**	**62**	**100.00%**

With the new sample, there are no big changes in the assets under management breakdown. 8.06% of the clients represent around 43.04% of the assets under management that we're studying, which means there is a big concentration of money in a small portion of our sample. On the other hand, 53.23% of the clients represent only 11.91% of the assets under management in question. These numbers still do not say much and have no significance to our study because we're not focusing on weighted portfolio figures but on each portfolio individually.

We then ran again a regression for Equation 2 on both LREALVOL35 and LREALVOL29 using this new sample. The result was a completely different picture.

We observed a clear relationship between perceived volatility (PROFILEVOL) and the logarithm of the real 35 month volatility (LREALVOL35) and, in terms of each profile, we observed individual adherence on all profiles tested against real 35 months volatility (LREALVOL35).

To clarify, we can see below Equations 3 and 4:

Equation 3

$$LREALVOL35 = \beta 1 + \beta 2\ PROFILE1 + \beta 3\ PROFILE2 + \beta 4\ PROFILE3 + \beta 5\ PROFILE4 + \upsilon$$

Equation 4

$$LREALVOL35 = \beta 1 + \beta 2\ PROFILEVOL + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:32
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.698305	0.298372	-5.691897	0.0000
PROFILE1	-1.914263	0.353039	-5.422242	0.0000
PROFILE2	-1.269732	0.311075	-4.081760	0.0001
PROFILE3	-1.000339	0.311640	-3.209922	0.0022
PROFILE4	-0.752679	0.326851	-2.302822	0.0250

R-squared	0.435269	Mean dependent var	-2.800070
Adjusted R-squared	0.395639	S.D. dependent var	0.542782
S.E. of regression	0.421962	Akaike info criterion	1.189405
Sum squared resid	10.14897	Schwarz criterion	1.360948
Log likelihood	-31.87157	Hannan-Quinn criter.	1.256758
F-statistic	10.98325	Durbin-Watson stat	1.944206
Prob(F-statistic)	0.000001		

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:32
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.447024	0.118376	-29.11922	0.0000
PROFILEVOL	7.781024	1.264360	6.154123	0.0000

R-squared	0.386962	Mean dependent var	-2.800070
Adjusted R-squared	0.376745	S.D. dependent var	0.542782
S.E. of regression	0.428507	Akaike info criterion	1.174708
Sum squared resid	11.01711	Schwarz criterion	1.243326
Log likelihood	-34.41596	Hannan-Quinn criter.	1.201649
F-statistic	37.87323	Durbin-Watson stat	1.866629
Prob(F-statistic)	0.000000		

As we can see on the left, we observed a significant relationship between the logarithm of the real 35 months volatility (LREALVOL35) and the perceived volatility (PROFILEi). In the first regression, we used 4 dummy variables and the coefficients are statistically significant (only marginally for the coefficients of PROFILE4). More important, the estimates are easily interpreted and in line with our expectation.

In the second regression (Equation 4) we used the “theoretical” figures of the volatility in each level and also obtained a significant relationship between the logarithm of real volatility (LREALVOL35) and perceived (PROFILEVOL).

It is important to note that, statistically speaking, Equation 4 corresponds, to a re-estimation of Equation 3 but, instead of dummy variables representing the profiles, we imposed pre-defined values for perceived volatility.

As a final comment, the signal of the PROFILEVOL coefficient is, as expected, positive.

To be more explicit, we can compare, using the first regression results, the expected real volatility in each level with the mid value of each class of the questionnaire.

Profile	**1**	**2**	**3**	**4**	**5**
Number of Observations	5	23	22	10	2
Mid-Value	1.5%	5.0%	9.5%	14.5%	19.5%

Expected Volatility (Equation 3)	2.7% (*)	5.1% (**)	6.7%	8.6%	18.3%
Expected Volatility (Equation 4)	4.0%	5.2%	7.4%	10.9%	16.1%

(*) $e^{-1.698305}$, (**) $e^{-1.698305} \times e^{-1.914263}$

Going a bit deeper into this analysis, we can make Wooldridge (2003) correction to coefficient to the value of intercept C (in this case the expected value of the volatility for the clients with Profile 5). We calculate it as follows:

$$e^{-1.698305} \times e^{\frac{0.421962^2}{2}} = 20.0\%$$

To obtain the value for other clients we must multiply this value by the exponential of each coefficient. By doing so, we obtain the following.

Profile	**1**	**2**	**3**	**4**	**5**
Number of Observations	5	23	22	10	2
Mid-Value	1.5%	5.0%	9.5%	14.5%	19.5%
Expected Volatility (Equation 3)	2.9%	5.6%	7.4%	9.4%	20.0%
Expected Volatility (Equation 4)	4.4%	5.7%	8.1%	12.0%	17.7%

For Equation 3, results are consistent but we can point out that it is observable an important jump from Profile 4 to Profile 5. As a note, there are only two observations in Profile 5 but, the observed values are acceptable.

Regarding Equation 4, as expected, it shows more fit than Equation 3 when comparing the mid-values for Profiles 3 and 4 but, at the expense of a lower fit for the other risk profiles.

Consistent on both Equations is the fact that expected volatility tend to be higher than the mid-values on the lower profiles and lower than the mid-values on the higher profiles (Profile 3 and especially on Profile 4). Profile 5 has only 2 observations and in both cases its' expected volatility is more or less in line with the mid-values.

We also tested these equations with 29 months volatility data and the results were very similar, proving little importance for the difficult market conditions in terms of the relationship between perceive and real volatility.

These results are interesting. We can conclude that the financial institution in question, using this questionnaire to assert the risk profile for its affluent/private banking retail network, will be doing an acceptable job for around 72% of its clients (62 divided by 86). For the other 28%, this questionnaire will not help the financial institution in selling "appropriate" and "suitable" products to its clients.

There can be several explanations for the results of this 28% of the sample. They might have lied when answering the questionnaires, giving wrong indications to the model and jeopardizing its results (they might have done this consciously or unconsciously). On the other hand, they might just have no clue about the average risk that they incur on their investments with the bank, thinking they have a certain degree of risk (having a certain perspective about risk) and really having a whole different risk in their portfolio (misreading real volatility). Of course this is always something that can be evaluated by the bank continuously and for sure, something that can be minimized with intensive and quality advisory because real volatility can always be monitored and compared to profile volatility on a regular basis. Acting actively on the differences will, on our opinion, reduce this portion of strange results to a lower percentage than 28%.

3.3 Multifactor Influence on Real Volatility

We proceed to the second objective of our study: to test the relationship of several variables (the ones most used on the questionnaires) with real volatility. In order to examine this relationship between the real volatility (taken from the statement) and 5 different variables (age, gender, degree of education, financial situation and investment experience), we tested different equations using the ordinary least squares method. For the purpose of studying these variables, we kept on using the 62 individual population which showed adherence on the previous tests.

3.3.1 Investment Experience

We initiate the test following with investment experience. Our first step was to analyse the answers to Question 2 which is directly related to clients' experience. This question has 5 possible answers from option 1 ("I have never invested") to option 5 ("I consider myself an experienced investor") but clients' options are very concentrated in option 2 ("I make some investments of relevant volume per year") as we can see in the following table.

Answer	**1**	**2**	**3**	**4**	**5**
Number of Observations	2	50	5	1	3
Average Volatility	3.0%	7.1%	7.7%	3.6%	10.5%
Standard Deviation	1.2%	4.4%	2.9%	-	3.9%

Our first conclusion is that the average volatility is growing up, as expected (the exception is answer 4 but as we only have one answer in this group, we disregard this observation).

As the average figures for volatility are in line with what was expected, we try different option (merging dummies and trying some transformations of the dependent variable. Our best result was the model defined by Equation 5. Using the real volatility as the dependent variable (REALVOL35) we tested it against the intercept (C), and the answer to question 2.

Equation 5

$$LREALVOL35 = \beta 1 + \beta 2\ Q2A2 + \beta 3\ Q2A3 + \beta 4\ Q2A5 + \upsilon$$

The interpretation of the coefficients is different. The expected value of the volatility for the clients which answer that they have never invested is 3.2% $\left(e^{-3.571315} \times e^{\frac{0.513430^2}{2}} \right)$ and to obtain the expected value for the other clients we must multiply this value by the exponential of each coefficient, i.e. we obtain 7.0%, 8.2% and 11.4% for answers 2, 3 and 5 respectively. We didn't estimate a coefficient for answer 4 since we had only one client choosing this option.

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 13:02
Sample: 1 61
Included observations: 61

	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.571315	0.296429	-12.04780	0.0000
Q2A2	0.782162	0.305192	2.562850	0.0130
Q2A3	0.932911	0.374956	2.488055	0.0158
Q2A5	1.268420	0.419214	3.025714	0.0037

R-squared	0.150308	Mean dependent var	-2.791350
Adjusted R-squared	0.105587	S.D. dependent var	0.542890
S.E. of regression	0.513430	Akaike info criterion	1.567918
Sum squared resid	15.02577	Schwarz criterion	1.706336
Log likelihood	-43.82149	Hannan-Quinn criter.	1.622165
F-statistic	3.361033	Durbin-Watson stat	1.882577
Prob(F-statistic)	0.024824		

As we can see on the left, we observed a significant relationship between the logarithm of the real 35 months volatility (LREALVOL35) and investment experience, not taking into account answer 4 due to insignificant number of observations.

By looking at the results and the meaning of the option "I make some investments of relevant volume per year" and "I make some investments of relevant volume per month", we can conclude that Q2A2 and Q2A3 could be merged. If we put these two together, we see that we cannot reject the possibility of the coefficients of alternatives Q2A3 and Q2A3 being equal and we obtain a better fit.

Using the logarithm of real volatility as the dependent variable (LREALVOL35) we tested it against the intercept (C), and the answer to question 2 but putting together Q2A2 and Q2A3 (we'll call this Equation 6):

Equation 6

$$LREALVOL35 = \beta 1 + \beta 2\ Q2A23 + \beta 3\ Q2A5 + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 13:02
Sample: 1 61
Included observations: 61

	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.571315	0.294871	-12.11147	0.0000
Q2A23	0.795866	0.302806	2.628306	0.0110
Q2A5	1.268420	0.417010	3.041702	0.0035

R-squared	0.144466	Mean dependent var	-2.791350
Adjusted R-squared	0.114965	S.D. dependent var	0.542890
S.E. of regression	0.510731	Akaike info criterion	1.541982
Sum squared resid	15.12907	Schwarz criterion	1.645795
Log likelihood	-44.03045	Hannan-Quinn criter.	1.582667
F-statistic	4.896966	Durbin-Watson stat	1.876352
Prob(F-statistic)	0.010836		

As we can see on the left, we not only observed a significant relationship between the logarithm of the real 35 months volatility (LREALVOL35) and investment experience putting questions 2 and 3 together, still not taking into account answer 4 due to insignificant number of observations.

We can generalize this approach using the complete sample (note that we had to delete one observation as the observed volatility was zero and we also delete the only observation where Q2A4 equals 1) and obtain similar but slightly higher figures about the expected volatilities: 3.7%, 7.8%, 9.3% and 12.4% for answers 1, 2, 3 and 5 respectively for the first regression. However, the fit is significantly poorer as we could expect if we assume that some clients do not answer correctly the questionnaire. Using the whole sample, merging the options 2 and 3 is rejected, at the 5% level.

We also tested Equations 5 and 6 with 29 months volatility data and the results were very similar, allowing us to extend the same conclusions to 29 months real volatility data.

To conclude on the investment experience, if we consider the only observation of Q2A4 as a sample error, we can conclude that investment experience is linked to real volatility.

The higher the experience the more volatility one takes on its portfolio. This is perfectly in line with the questionnaire scoring system, which attaches more points to higher experience and a lower number of points to lower experience. This is also in line with common sense. If you are an experienced investor, presumably you understand better the way the markets work and you feel more comfortable with risk, accepting higher risk you your portfolio.

However, grouping answers Q2A2 and Q2A3 we can get even better results. We can see that it is somewhat irrelevant if people make investments of relevant volumes yearly, monthly or even weekly. The major differences are between those who never invested, those who invest but are not experienced investors and experienced investors and, following this order, there is an increasing appetite for risk on the portfolios.

3.3.2 Education

We continue our study, testing education. This has been a theme under great discussion lately. Some literature refers that high school graduates, exhibit a greater tendency to accept risk than those without a high school diploma, but a lesser tendency than those possessing a college degree[1].

One other study reached the conclusion that economists are more prone to hold stocks than people with other kinds of education. It referred informational advantages as one of the main biases to this behaviour[2]. With these results in mind, one should expect that more educated people should be more prone to take risks that less educated people.

On our study, our first step was to get a closer look at the answer to Question 4, which we can see in the table below.

Answer	**1**	**2**	**3**	**4**
Number of Observations	5	13	43	1
Average Volatility	6.66%	5.01%	7.59%	10.90%
Standard Deviation	3.73%	2.31%	4.71%	-

[1] Vide Bellante & Green (2004)

[2] Vide Christiansen et al (2004)

We can observe that the breakdown of the answers is not well distributed. Just one individual chooses option 4 and there is a big concentration of answers in options 2 (“High School”) and 3 (“Degree / Post Graduation”). This is somewhat expected having in mind the client base but, for the purpose of this study, imposes some limitations on testing the education effect.

The averages are not very different which leads us to think that this will not be a determinant factor to the explanation of the real volatility figures. Using the logarithm of the real volatility as the dependent variable (LREALVOL35) and testing it against the intercept (C), and the answer to question 4 (we’ll call this Equation 7):

<u>*Equation 7*</u>

$$LREALVOL35 = \beta 1 + \beta 2\ Q4A2 + \beta 3\ Q4A3 + \beta 4\ Q4A4 + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:33
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.888674	0.235761	-12.25254	0.0000
Q4A2	-0.208800	0.277419	-0.752652	0.4547
Q4A3	0.175256	0.249091	0.703582	0.4845
Q4A4	0.671866	0.577495	1.163416	0.2494

R-squared	0.103062	Mean dependent var	-2.800070
Adjusted R-squared	0.056669	S.D. dependent var	0.542782
S.E. of regression	0.527178	Akaike info criterion	1.619784
Sum squared resid	16.11917	Schwarz criterion	1.757019
Log likelihood	-46.21332	Hannan-Quinn criter.	1.673666
F-statistic	2.221481	Durbin-Watson stat	1.805338
Prob(F-statistic)	0.095264		

The variables have no significance on the model (keep in mind that we have only one answer for option 4).

The F-statistic does not pass with a significance level of 2.5%, which means that there is lack of fit of the data to the estimated values of the regression.

The p-values are way too big (except for Q4A4, which means we cannot reject the possibility of the coefficients being null.

With Equation 7, we confirm that our intuition was correct. Education is not a determinant factor to the explanation of the real volatility figures. On our numbers, there is no relationship that can be extrapolated from education to risk appetite. Having these results in mind we also tested equations, we also tested combinations of Question 4 (“Education”) with Question 5 (“Education in Finance”). At first sight, these two questions together should have some explaining power on volatility but, in reality, the results pointed to the opposite.

To conclude on education, we tested Equation 7 with 29 months volatility data and the results were consistent with the ones obtained with 35 months data.

3.3.3 Gender

We move on to test if there is a relationship between the gender and real volatility. Using the logarithm real volatility as the dependent variable (LREALVOL35) and testing it against the intercept (C) and gender (MALE) (we'll call this Equation 8):

Equation 8

$$LREALVOL35 = \beta 1 + \beta 2\ MALE + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:33
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.892445	0.128217	-22.55889	0.0000
MALE	0.130165	0.152201	0.855220	0.3958

R-squared	0.012043	Mean dependent var	-2.800070
Adjusted R-squared	-0.004423	S.D. dependent var	0.542782
S.E. of regression	0.543981	Akaike info criterion	1.651920
Sum squared resid	17.75490	Schwarz criterion	1.720538
Log likelihood	-49.20953	Hannan-Quinn criter.	1.678861
F-statistic	0.731401	Durbin-Watson stat	1.899800
Prob(F-statistic)	0.395832		

The variable has no significance on the model

The F-statistic does not pass with a significance level of 2.5%, which means that there is lack of fit of the data to the estimated values of the regression.

If you talk to any salesman working the affluent or private banking retail client markets, you'll hear that men are more prone to taking risks than women. With this approach, we prove that this is very questionable. Again it is completely random. It is important to refer that our sample is not very well balanced. We had data for 62 men and 24 women, which we reduced to 45 men and 17 women with the adjustments referred on 3.2, which could generate a little bias since we have more almost 3 times more men than women. Anyway, we believe that our findings are consistent.

We tested Equation 8 with 29 months volatility data and the results were consistent with the ones obtained with 35 months data.

3.3.4 Financial Situation

Moving on to financial situation, people might expect rich people to take more risks than poor people. In this study, there might be a little bias because we are focusing on the affluent and private banking segments and not in mass market. However, in our tests, we found that this relationship is not correct.

In Question 9, there are 8 answers for option 1 (“Less than € 25.000”), 25 answers for option 2 (“Between € 25.000 and € 50.000”) and 29 answers for option 3 (“More than € 50.000”). To illustrate see table below.

Answer	**1**	**2**	**3**
Number of Observations	8	25	29
Average Volatility	5.50%	6.16%	8.20%
Standard Deviation	2.18%	3.50%	5.10%

Using the logarithm of the real volatility as the dependent variable (LREALVOL35) and testing it against the intercept (C), and the answer to question 9 (we’ll call this Equation 9), we found that there was no relationship between financial situation and real volatility.

Equation 9

$$LREALVOL35 = \beta 1 + \beta 2Q9A2 + \beta 3Q9A3 + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:34
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.996269	0.187226	-16.00349	0.0000
Q9A2	0.073482	0.215106	0.341610	0.7339
Q9A3	0.356115	0.211479	1.683921	0.0975

R-squared	0.079352	Mean dependent var	-2.800070
Adjusted R-squared	0.048143	S.D. dependent var	0.542782
S.E. of regression	0.529555	Akaike info criterion	1.613618
Sum squared resid	16.54528	Schwarz criterion	1.716544
Log likelihood	-47.02215	Hannan-Quinn criter.	1.654029
F-statistic	2.542631	Durbin-Watson stat	1.950637
Prob(F-statistic)	0.087251		

The F-statistic does not pass with a significance level of 2.5%, which means that there is lack of fit of the data to the estimated values of the regression.

The coefficient of Q9A2 (“Between € 25,000.00 and € 50,000.00 of regular annual income) is not statistically significant but the coefficient of Q9A3 (“More than € 50,000.00 of regular annual income”) is marginally significant.

In order to clarify the significance of the Q9A3 we estimate what we’ll call Equation 10 and we conclude that this group of clients has a statistically different behaviour from the other groups, showing more volatility, which is, in fact, what we were expecting to see.

Equation 10

$$LREALVOL35 = \beta 1 + \beta 3Q9A3 + \upsilon$$

Dependent Variable: LREALVOL35				
Method: Least Squares				
Date: 11/17/09 Time: 12:34				
Sample: 1 62				
Included observations: 62				
	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.940601	0.091503	-32.13679	0.0000
Q9A3	0.300446	0.133792	2.245619	0.0284
R-squared	0.077531	Mean dependent var		-2.800070
Adjusted R-squared	0.062156	S.D. dependent var		0.542782
S.E. of regression	0.525643	Akaike info criterion		1.583336
Sum squared resid	16.57801	Schwarz criterion		1.651953
Log likelihood	-47.08341	Hannan-Quinn criter.		1.610277
F-statistic	5.042803	Durbin-Watson stat		1.998513
Prob(F-statistic)	0.028424			

The variables have no significance on the model

The F-statistic does not pass with a significance level of 2.5%, which means that there is lack of fit of the data to the estimated values of the regression.

We also tested Equations 9 and 10 with 29 months volatility data and the results were consistent with the ones obtained with 35 months data.

3.3.5 Age

Finally, we'll test age. There are several papers written on this matter and again, everybody in the market will tell you that older people are more risk averse than younger people. In our study, we found no relationship between age and real volatility.

This is more important as we are studying a sample of 62 people with an average age of 56.3 where the youngest individual is 22 and the oldest is 85 years old (compares with the initial sample of people with an average age of 55.6 years where the youngest individual was 20 and the oldest 86 was years old). It's a well balanced sample and in our opinion, representative of the segment we're studying.

We tested several approaches to age, namely age ranges, quadratic functions, etc. but there were really no significant results.

As we have done so far, we used the logarithm of the real volatility as the dependent variable (LREALVOL35) and tested it against the intercept (C) and age (AGE) (we'll call this Equation 10):

Equation 11

$$LREALVOL35 = \beta 1 + \beta 2\,AGE + \upsilon$$

Dependent Variable: LREALVOL35
Method: Least Squares
Date: 11/17/09 Time: 12:34
Sample: 1 62
Included observations: 62

	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.825022	0.311411	-9.071675	0.0000
AGE	0.000440	0.005351	0.082199	0.9348

R-squared	0.000113	Mean dependent var	-2.800070
Adjusted R-squared	-0.016552	S.D. dependent var	0.542782
S.E. of regression	0.547255	Akaike info criterion	1.663924
Sum squared resid	17.96931	Schwarz criterion	1.732541
Log likelihood	-49.58165	Hannan-Quinn criter.	1.690865
F-statistic	0.006757	Durbin-Watson stat	1.924310
Prob(F-statistic)	0.934762		

The variables have no significance on the model.

The F-statistic does not pass with a significance level of 2.5%, which means that there is lack of fit of the data to the estimated values of the regression.

On our study we tested several approaches to the study of age, namely breakdown of the population by age ranges, quadratic functions of age, etc. but, we neve achieved significant adherence results.

To conclude on age, we tested Equation 10 with 29 months volatility data and the results were consistent with the ones obtained with 35 months data.

3.4 Final Comments

Just to finalize, despite not being the main objective of Section 3.3, we've also tested an equations using combinations of the variables we tested against real volatility and the result was, as expected, that together none works and only the investment experience questions shows real significance.

For all of this regressions in section 3.3, we also tested results for REALVOL29 instead of REALVOL35 and, in all cases, the results were similar.

As for the studies on section 3.1, we saw no difference when taking out data from a very specific market environment characterized by high volatility, abnormal price behavior on the most important asset classes and by a sudden drop in confidence.

In such a difficult market environment, 6 difficult months could, at first glance, be expected to have an impact on how people behave and affect their attitude towards risk or their perception of risk. It could be that 6 months is not enough time for the retail market to react but is still an interesting indication of sensitivity of affluent and private banking retail clients to extreme events.

4. Conclusion

On the first part of this study, we have examined the relationship between real volatility and perceived volatility. We initiated our study using the 86 questionnaires that we managed to get from the financial institution that allowed us to develop this study, we analysed the data and ran several regressions. In our first step, analysing both 35 month and 29 month volatility data, we found no evidence of relationship between perceived and realized volatility.

Surprised by these results, we decided to adjust our sample by widening the volatility ranges by half of each of the downward and upward limits and excluding from the study, observations where 35 months historical volatility was situated outside these new ranges. With these simple adjustments, we found a consistent relationship between real volatility (REALVOL35) and perceived volatility (PROFILEVOL).

Behavioural finance has for sometime been enhancing the relevance of cognitive psychology[3]. Individuals tend to reveal some patterns in their behaviour: people tend to like simple things, tend to be overconfident about their abilities, tend to se separate decisions that should be made in aggregate, tend to put to much weight on short term occurrences, tend to avoid to realize losses much more than to realize gains, etc. These are just a few dispositions that might explain this referred lack of relationship between real and perceived volatility when we take the 86 questionnaires instead of the adjusted 62. These 28% of the clients that we took out of the study show no pattern on their behaviour. The real volatility (REALVOL35) found on the statements has no relationship at all with the perceived volatility (PROFILEVOL), accepted by the client when signing the questionnaire results. We can argue for several justifications to this finding.

Our best guess to explain this is that people are confident that they accept a determined level of risk but, in fact, they have no idea of their risk profile. In fact, their risk profile probably changes a lot over time, running along with economic cycles[4], being an interest theme for future studies, possibly by repeating the analysis on the study in a future time frame. We do not have data to back this up (because we do not possess historical data for the same sample) but, it is a big possibility that people

[3] Vide Ritter (2002) and Barberis & Thaler (2002)

[4] Vide Shiller (2000)

accept more risk in bull markets and less risk in bear markets, with their risk profile change somewhat rapidly in the middle.

One other big point to make is that, in their commercial activity, financial institutions tend to be product pushers. Individuals are consistently tempted with new innovative products and, end up buying the ones that they find most appealing, possibly neglecting product specific risk and potential diversification benefits. Having these variables in mind, it is difficult to believe people are actually 100% rational when making decisions. It is even more difficult to believe that people can actually process all the information they have available in order to make a rational decision.

In this context, is seems plausible that people do not lie when accepting a risk profile. They really believe that they are accepting their risk profile. However, when making a real investment decision, they end up being influenced by a big number of factors, creating a bias between their perceived volatility and what in fact is their real volatility.

In adjusting for the 62 questionnaires, it allowed us to subtract the observations where real volatility (REALVOL35) was clearly misadjusted with profile volatility (PROFILEVOL). When we take the adjusted 62 questionnaires sample, we see a clear relationship between 35 month volatility (REALVOL35) and perceived volatility (PROFILEVOL) and we also observe individual adherence of each profile (PROFILEi) with real volatility (REALVOL). For this 72% of the population, the questionnaire used by this financial institution does a pretty good job in the client profile classification, providing a strong base for work on good advisory or in other words, for selling “suitable” and “appropriate” products to the clients.

On the second part of our study, we studied the impact of several factors (age, gender, degree of education, financial situation and investment experience) on real volatility. These are important variables to study, especially because risk profile questionnaires have become a sort of commodity and these 5 factors a part of this commodity.

Again, our findings were somewhat surprising at first glance but natural when you take a deeper look. When you start thinking about the impact of each and every one of these factors on real volatility, you tend to rationalise things. However, it is a mistake to rationalise human behaviour[5]. When studying

[5] Vide Van Neumann and Morgenstern (1947) and Ritter (2002)

these factors individually, we cannot take into account several circumstances which might make a difference. We're talking about factors like liquidity, health, family, access to information, etc.

As an exercise, if we take education as an example, one would think that people with a higher degree of education would have a bigger appetite for risk than people with a lower degree of education[6]. On the other hand, people with a lower degree of education might be more vulnerable to its financial advisers offers. Making these assumption looks relatively clean but, when making it, we are not taking into account the area of expertise, the liquidity condition of the individual, the family situation of the individual, the age of the individual, etc. Putting it together is very difficult because you need a whole lot of information that is not widely available and, if available, we have to keep in mind that it might change a lot over time.

We could do this exercise for every one of these factors and we could always find room for uncertainty. In reality, on our regressions, just investment experience, individually or together with other factor showed correlation with real volatility (REALVOL35). On investment experience, we can see clearly that the higher the experience, the more volatility one takes on the portfolio. Being an experienced investor you actually accept more risk.

We see no relationship between age, gender, education and financial situation with real volatility (REALVOL35). These results are somewhat surprising and contradict some of the literature on the matter.

Just as a closing note, if you take the results of this study together, we can get to an interesting finding towards recent regulation. It is important to apply the measures specified by Markets in Financial Instruments Directive (MiFID), and especially follow the regulatory lead towards a successful "suitability" or "appropriateness" test for a specific investment product. Globally, the results of using a questionnaire do work and can be useful for banks to create more adequate and suitable product/client approaches.

Of course not everything in the new regulation is perfect but, at least, it is a good step in the right direction on the great objective of selling the right products to the right clients, elevating client satisfaction and consequently, profitability.

[6] Vide Bellante and Green (2004)

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6. Appendix

6.1 Appendix 1 – Risk Profile Questionnaire used for this study

1st Module – Knowlegde and Experience

1st Question: Until present, which was the riskiest investment that you made?

Possible Answers:

1) Mixed Assets (including convertible bonds and preferred shares)
2) Structured Products (capital protected or capital guaranteed)
3) Bonds (including international, corporate or high yield bonds)
4) Equity (domestic or foreign equities)
5) Money Market Funds or Time Deposits
6) Derivatives, Commodities or Private Equity
7) Have not made any of these kinds of investments up until the present date

2nd Question: What is your investment experience?

Possible Answers:

1) I have never invested
2) I make some investments of relevant volume per year
3) I make some investments of relevant volume per month
4) I make some investments of relevant volume per week
5) I consider myself an experienced investor

3rd Question: What is the relationship of your present or prior job with the financial sector?

Possible Answers:

1) No relation whatsoever
2) Slightly related
3) Strongly related
4) I work in the financial sector

4th Question: What is your level of education?

Possible Answers:

1) Junior high school
2) High school
3) Degree / Post Graduation
4) None of the above

5th Question: Do you have any specific education in finance?

Possible Answers:

1) No
2) Yes

2nd Module – Financial Situation

6th Question: What percentage of your assets is invested in liquid assets (equities, bonds, mutual funds, time deposits, structured products)?

Possible Answers:

1) Up to 25%
2) Up to 50%
3) Up to 75%

4) More than 75%

7th Question: Your investments with our financial institution … do you consider that they might represent an important percentage of your total assets (including real estate) or of your regular financial commitments?

Possible Answers:

1) More than 50%
2) Between 20% and 50%
3) Less than 20%

8th Question: What is you main source of income?

Possible Answers:

1) Rents
2) Retirement
3) Own business
4) I have no regular source of income
5) Salary

9th Question: What is the level of your regular annual income?

Possible Answers:

1) Less than € 25.000
2) Between € 25.000 and € 50.000
3) More than € 50.000

<u>3rd Module – Investment Objectives</u>

10th Question: What is your investment objective?

Possible Answers:

1) Liquidity
2) Retirement
3) Regular income
4) Speculation
5) Saving or no specific objective

11th Question: To your investment objective stated on the last question, what is your maximum time horizon?

Possible Answers:

1) Up to 1 year
2) Between 1 and 3 years
3) Between 3 and 5 years
4) Between 5 and 10 years
5) More than 10 years
6) No term defined

12th Question: Imagine that 12m Euribor is at 3%. What is your preferred return scenario for a 1 year investment?

Possible Answers:

1) Obtain up to 3% guaranteed
2) Obtain up to 8% but running the risk of making nothing
3) Obtain up to 15% but running the risk of losing up to 5%
4) Obtain up to 24% but running the risk of losing up to 12%
5) Obtain up to 32% but running the risk of losing up to 18%
6) I don’t know

13th Question: Imagine that your investment presents a negative return. What would you do?

Possible Answers:

1) I would not accept any loss on my investment, even if temporary
2) I would stop loss at 5%
3) I would stop loss at 10%
4) I would stop loss at 15%
5) I would stop loss at 20%
6) I don’t know

6.2 Appendix 2 – Risk Profile Questionnaire from Citibank Belgium

1st Question: How long do you intend to remain invested (when do you think you need your capital)?

Possible Answers:

1) < 2 years
2) 2 – years
3) > 5 years

2nd Question: What would you like to plan for?

Possible Answers:

1) Specific financial goals or major purchases
2) Retirement income
3) Long term wealth creation

3rd Question: Your investment experience is best described as follows:

Possible Answers:

1) Limited: I have very little investment experience outside of bank savings accounts and time deposits. Slightly related
2) Moderate: I have some experience investing
3) Extensive: I am an active and experienced investor

4th Question: How will you describe your expected future income over the next 5 years?

Possible Answers:

1) I expect my income to increase
2) I expect my income to remain steady
3) I expect my income to decrease

5th Question: Thinking about the decisions you made about your personal finances, how would you describe yourself?

Possible Answers:

1) Very cautious
2) Generally cautious
3) A moderate risk taker
4) An aggressive risk-taker

6th Question: Please indicate the total amount that you would like to invest/save with Citibank including your current savings/investments in the bank?

Possible Answers:

1) < 75.000 EUR
2) 75.000 – 250.000 EUR
3) > 250.000 EUR

7th Question: If you have some experience of investing, what's your attitude to the performance of your investments in the past?

Possible Answers:

1) None of my investment have lost money
2) Although some of my investments underperformed, I am prepared to invest in products with similar risk levels again if I believe that they can achieve superior returns in the long run
3) Some of my investments underperformed so I am now more cautious towards investing in products with similar risk levels
4) Some of my investments underperformed so I have resolved to never place money in investments with similar risk levels

8th Question: Do you have 6 months to 1 year liquidity?

Possible Answers:

1) Yes
2) No

9th Question: What is the percentage of your total wealth (excluding property and business interests) that you would like to invest and/or save with Citibank?

Possible Answers:

1) Less than 50%
2) 50% - 75%
3) Greater than 75%