Price Setting and the Reluctance to Realize Losses in Apartment Markets

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Abstract

Using data on all real estate transactions in the greater Helsinki area during 1987 to 2003 (about 80,000 apartment transactions with capital gains available), we find substantial support for loss realization aversion. Further, a disproportionate number of sales occurred exactly at the original purchase price. Reluctance to realize losses is weaker with pricier apartments, seasoned sellers, and apartments that are likely bought for investment purposes. Mortgage down payment requirements are unlikely to fully explain the results. On the whole the results are consistent with loss aversion and mental accounting.

1. Introduction

For most people, the purchase of their own home represents the most significant financial investment they ever make. There are also many things to consider when selling a house and moving. There are direct transaction costs, but indirect costs, related to e.g. learning or rebuilding one's social network, are probably larger. Naturally there must be benefits as well, related to e.g. improved job or schooling locations. With the exception of forced liquidations, normatively these benefits should outweigh the costs whenever one moves. The purchase price of the new apartment, as well as the sale price of the old one, naturally play important roles in the cost calculation associated with the decision to move.

But what role does the purchase price of the old apartment play? First, mortgage down payment provisions could make it impossible to sell the old apartment even if the optimal (unconstrained) decision is to move (Stein 1995; Genesove and Mayer 1997). Second, according to prospect theory (Kahneman and Tversky 1979), loss-averse agents might consider the original purchase price to be a reference point in their value function. The empirical studies investigating the aversion to realize losses typically present this argument (see Odean 1998 and Grinblatt and Keloharju 2001 for a stock market context; Genesove and Mayer 2001 for a real estate context). Third, agents may engage in mental accounting and the associated need to break even (Shefrin and Statman 1985; Thaler and Johnson,1990). Fourth, people may believe in mean-reverting returns, and hence judge the expected return to be better for investments that have fallen (Andreassen 1988; Odean 1998).

With the exception of the mortgage down payment argument, a rational agent with a standard utility function would ignore the purchase price of the old apartment in the decision to move. Even an agent who believes in mean-reverting returns would ignore the purchase price, while still considering prior returns. The purchase price should therefore be treated as a sunk cost. I.e., while considering the sale price itself is important in decision-making, considering the sale price in relation to purchase price (i.e., return) is a form of sunk cost bias. Psychological loss realization aversion could thus have an adverse effect on decisions to move. It can lead to suboptimal decisions in the housing market, and, as a consequence, even in the labor market. Loss realization aversion could also cause the market to function less efficiently: Liquidity could dry up in an economic downturn when prices are low. This would hinder labor mobility at a time when it is most needed.

We analyze loss realization aversion in the greater Helsinki area apartment market, employing a unique and extensive panel data set. It includes all apartment transactions in the period of 1987-2003. The total number of transactions in the dataset is 309,314. The data provide the debt-free price for each transaction, as well as apartment specific attributes such as house type, location according to a zip code, total living area, number of rooms, etc. Having transaction data with various control variables is particularly valuable because so far only a few studies concerning the apartment market have used transaction data. To study the effect of capital gains/losses on selling propensity, we use a regression method similar in spirit to that of Grinblatt and Keloharju (2001). It allows the inclusion of many control variables, thus reducing the probability of spurious results due to omitted variables. Most importantly, it allows one to accurately control for general real estate market, as well as area-specific trends.

The paper contributes to the existing literature as follows. First, we show that apartment owners are reluctant to realize losses. This is in line with the studies from the stock markets (Odean 1998; Grinblatt and Keloharju 2001), as well as Genesove and Mayer's (2001) results from the real estate markets. Compared to Genesove and Mayer, our data cover a longer time period and contain about 14 times as many transactions with the return available.

Second, our results offer further insight into what is causing this loss realization aversion in the apartment market, namely regarding the mortgage down payment versus loss aversion hypotheses. Our results show that the down payment issue is probably not the only driver of loss avoidance. We show that even small losses are avoided after at least two years from purchase, when the loan to value ratio has decreased from the original, even if the apartment value has stayed the same. We also find strong loss realization aversion in cases where the mortgage constraint is less often binding. These are apartments that are likely bought for investment purposes, and the most expensive apartments. Nevertheless, it is impossible to tell for which sellers the down payment constraint is binding without data on loan balance.

Third, we find that a large number of apartments are sold exactly at the purchase price. These zero-return observations form an important part of the general loss realization aversion pattern. The results are consistent with the idea that sellers are trying to break even in their mental accounting, framing the purchase as a gain or loss in relation to the original purchase price. This could involve waiting for prices to go up before selling the apartment at a loss, or, on the other hand, easily accepting an offer equal to the purchase price, even if the fair value of the apartment were somewhat higher. We also identify other common reservation prices, corresponding to e.g. 50% and 25% returns.

The rest of the paper is organized as follows. Section 2 presents the institutional setting and introduces the data. Section 3 describes the methods and Section 4 presents the results. Section 5 provides a further discussion of the results, and Section 6 briefly concludes.

2. Institutional setting and data

The direct transaction costs in the Finnish real estate market consist of real estate agents' fees, and government taxes. Fees are typically 4-5% of the value of the transaction. The Finnish tax law stipulates an asset transfer tax of 1.6% in real estate transactions. However, first-time buyers are exempt from this tax. Apartment sales can be subject to capital gains taxation. Taxation depends on the holding period: Sales where the owner has lived in the apartment for more than two years are completely exempt from the capital gains tax, whereas other sales are fully taxed. The tax rate has varied between 25% and 29% during the sample period.

The data for the study were obtained from Statistics Finland, and include all apartment transactions in the greater Helsinki area from the beginning of 1987 to the end of 2003. Statistics Finland obtains the data from the Finnish tax authority which requires the seller and the buyer to fill out an asset transfer tax declaration when there is a change in the ownership of the apartment. In addition to the price of the apartment, the declaration provides other information related to the apartment and its new owner. Because the original source of the data is the tax authority, the data can be considered highly reliable.

The data are particularly valuable because in most studies of the apartment market only appraisal-based values, or the owners' own assessments of apartment value are available, and they often contain assessment errors (see e.g. Goolsby 1997; Kiel and Zabel 1999). Moreover, the data include all transactions that have taken place during a relatively long period in a market that can be considered relatively isolated and independent of other apartment markets in Finland.

There were approximately 970,000 inhabitants in the greater Helsinki area in 2003, of whom around 560,000 lived in the metropolitan Helsinki, and the rest in the adjacent cities of Espoo, Vantaa, and Kauniainen (Statistical Yearbook of the City of Helsinki, 2004). During the past decades, these four cities have grown into a single greater Helsinki area. Approximately 20% of the Finnish population live in the area. It is also the location of the majority of large corporations, leading universities, government and cultural institutions. At the end of 2000, there were altogether 465,943 apartments. The original data includes 309,314 transactions. Table 1 presents the breakup of these transactions by three-year periods and room count.

[Insert Table 1 about here]

The sample of transactions that we consider is constructed as follows. First, our main analysis requires calculation of realized returns for each apartment. Therefore, only apartments that were sold at least twice during the sample period are included in the sample. Second, some transactions are excluded due to missing, or clearly falsely recorded data. Third, housing types labeled as “other house built for living purposes”, “other house”, or “unknown house type” are excluded. Fourth, apartments in which the number of rooms or the living area changes from one transaction to another are discarded. As a result, the sample is reduced to 186,339 transactions. Of these transactions, 70,778 represent the first transactions of the given apartments in the original data. Because a cost basis for calculating return is lacking for these cases, they are not used in the analysis of the sale decision. The number of transactions with the return available is thus 115,561. The average holding period for an apartment is 5.6 years.

As mentioned, apartments held for less than two years are subject to normal capital gains taxation, while apartments held longer are completely exempt from the tax. This provides a strong incentive against holding periods of less than two years. Such transactions nevertheless do occur, but the situation of the seller is likely to be somehow unusual. Due to their special nature we excluded these transactions from the analysis of the sale decision. This leaves 79,483 transactions for the analysis of the sale decision.

Figure 1 presents a constant-quality apartment price index (hedonistic index).[1] The volatility of apartment prices over time is evident in the Figure. The overall Helsinki area

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[1] This index is constructed from monthly dummies of the regression model of Table 2. The details of this model are discussed in the next section.

market suffered from a longer decline in 1989-1993, and shorter declines in 1995-1996 and 2000-2002.

[Insert Figure 1 about here]

3. Methods

Studying loss realization aversion in the apartment market presents some methodological challenges. First, it is well known that the volume of trade and price levels exhibit a strong positive correlation in real estate markets (see e.g. Stein 1995). This must be taken into account to avoid false conclusions about the impact of losses on the likelihood of a sale. Second, there are generally more opportunities to realize gains than losses. Third, as opposed to a portfolio of stocks, people usually own only one apartment. The realized return from the apartment cannot be compared to a "paper" return from other apartments held by the same person. Fourth, apartment market prices are observable only at the time of the transactions, which occur infrequently. For example, in 2000, only 3.7% of the total apartment stock were traded during the greater Helsinki area.

We use a regression method similar in spirit to that of Grinblatt and Keloharju (2001). The main advantage of this method is that it allows the inclusion of many control variables, thus reducing the probability of spurious results due to omitted variables. Below we first give a brief example of this method, and then explain how we tackle the four problems presented above.

In the method of Grinblatt and Keloharju (2001) a binary dependent variable takes the value of 1 for a stock if a sale occurs during a day, and 0 otherwise. Each day when an investor decides to sell any stocks, all other stocks in his portfolio are examined and classified into sales and non-sales. As an example, consider an investor with three stocks in his portfolio, labeled A, B, and C. During a day *t*, he sells stocks A and B, but not C. Three observations are now recorded, and the dependent variable receives the value of 1 for stocks A and B, and the value of 0 for stock C, for that particular day. The returns are calculated based on actual transaction prices for stocks A and B (realized returns), and based on the purchase price and stock market closing price for stock C (paper return). This return, along with other explanatory variables, is then used to explain the sell versus hold decision.

To avoid the confounding effect of the correlation between prices and volume, our regressions include fixed time effects. We also include the interactions of these effects with zip code level area effects. Any general market price movements, as well as area specific trends, are controlled for by this technique. These controls also allow the data to have disproportional numbers of realized gains to losses without impacting inference.

Grinblatt and Keloharju (2001) approximate the points in time when investors make selling decisions by observing the timing of actual sales. This is of course not entirely accurate, because investors could also be making decisions that result in no actions. An alternative is to make observations at specific intervals, and this is a route we take. We use monthly intervals. The fact that people usually own only one apartment thus does not present a problem in this respect. However, the degree of control is even greater in the context of a stock portfolio, as the econometrician can observe which stock is sold, given that something is sold. The method still works with one asset, and investors with exactly one stock form a major group in the study of Grinblatt and Keloharju (2001).

To be able to calculate returns each month, we estimate apartment values for each month between the actual sales. As an example, consider an apartment first bought on June 5, 1994, and sold on July 18, 1996. There are 25 full months between these two transactions. For each month *t* between the sales, a paper return for the apartment is calculated based on the actual buying price, and an estimated month *t* value. As a result, 24 observations are recorded with the dependent variable having a value 0 (not a sale) and one observation with a value 1 (the actual sale in 1996). The return for the sale in 1996 is again based on actual transaction prices.

Apartment values are estimated with a regression explaining the apartment's debt-free price per square meter (see, e.g., Case and Shiller 1987). The model coefficients are estimated on the sample of 186,339 transactions. Apartment characteristics used as independent variables are the following: a dummy for social financing, apartment age (in months), apartment area (in square meters), number of rooms, and housing type dummies (row house and single-family houses; condominium apartment is the omitted category). In addition to apartment specific characteristics, we include area fixed effects at the level of zip code which contain important value relevant information. The original data cover 175 zip code areas, and there are on average 1,065 transactions in each zip code area. However, there is substantial variation in the number of transactions across areas, and we combine small zip code areas having less than 250 transactions with adjacent zip code areas. We thus arrive at 114 areas in our analysis.

To capture any long-term trends in the relative prestige of different areas, these zip code effects are interacted with dummies indicating the years 1987-1992, 1993-1998, and 1999-2003. To control for movements in general market valuation, monthly dummies for each month (except one) during the sample period are included. We use a logarithm transform of the dependent variable to reduce skewness and to achieve more stable estimated prices. The model is estimated by OLS.

Table 2 presents the results of this appraisal regression. The model gives intuitively appealing results: socially financed apartments are cheaper than apartments funded with market financing; larger apartments (both by the number of rooms, and by total area) have lower prices per square meter; single-family houses are more expensive than row houses, which in turn are more expensive than condominium apartments. This is expected because the price of the single-family houses and row houses includes also the lot in addition to the apartment, and the size of the lot is on average greater in the case of single-family houses. The pure aging effect (i.e., incremental reduction in price for each additional year in building age) is EUR 2.4 according to the model. This value seems rather small, but it could be due to the fact that we do not have data on the physical condition of the apartments. Value enhancing restructuring and improvements cannot be controlled for in the model, and thus the apartment's age coefficient gets a negative value that may be too small. In addition, in some cases when the apartment becomes old enough, its age may become a valuable feature. However, as these cases are quite rare, the lack of the apartment's condition variable is most likely the main reason for the low value of the age coefficient. Despite the lack of a measure of physical quality, the model explains as much as 85% of the variation in apartment prices.

[Insert Table 2 about here]

We use the predicted values from the regression as a base for the estimate of apartment value each month between sales. We then measure the estimation errors at the point of the actual sales. The final estimated price is obtained by fixing the estimation errors at zero in both sales, and linearly smoothing the errors over the intermediate months, i.e.,

$$
\begin{aligned}
P_k^E &= P_k^R - \left(\frac{T-k}{T-t} \varepsilon_1 + \frac{k-t}{T-t} \varepsilon_2 \right) \\
\varepsilon_1 &= P_t^R - P_t^S \\
\varepsilon_2 &= P_T^R - P_T^S
\end{aligned}
\qquad (1)
$$

where

P_k^E = estimated price for month k

P_k^R = price predicted by the regression model for month k

P_k^S = actual sale price for month k

t = numbered month of the first transaction

T = numbered month of the second transaction

K = index of the month between t and T

After an apartment is first sold, it appears as an observation each month until the end of the sample period. The apartment characteristics are the same for these ‘hold’ observations and the actual transactions. The return for the hold observations is calculated based on the estimated value, whereas for the sale transactions it is the actual return. The total number of hold observations is 6,468,604. This is much larger than the number of sell transactions, reflecting the much longer holding periods of the apartments relative to the monthly interval. The total number of observations in the analysis of the sell decision is thus 6,566,087 (79,483 sale decisions and 6,468,604 hold decisions).

Because of the large number of observations, running a logistic-regression is not computationally feasible. We therefore use an OLS regression. Using OLS for a binary choice model such as this may cause the disturbance term to be heteroskedastic. Moreover, the OLS model may predict probabilities of greater than one or less than zero. However, due to the very large sample size, the OLS results are very likely robust.

4. Results

4.1. The propensity to sell at a loss

As we aim to find out whether the probability to sell an apartment changes when one is facing losses, a loss dummy representing negative returns is set up as the main explanatory variable in the regressions. This dummy obtains a value of 1 when the current apartment price indicates a loss, and 0 otherwise. In addition, to avoid obtaining spurious results due to omitted variables, we use the apartment characteristics as control variables, similarly to the hedonistic price estimation regressions explained in Section 3. These variables are the following: a dummy for social financing, apartment age (in months), apartment area (in square meters), number of rooms, and apartment type dummies (row house and single-family houses; condominium apartment is the omitted category). Similar to the price regression, we also include area fixed effects at the level of zip code (114 zip code areas), and time effects in the form of monthly dummies. In addition, we include the following new variables: the housing corporation's debt per area (except for the years 1999 and 2000 where data are not available), a dummy for first-time apartment buyers (except for years 1987 and 1990 where data is not available), and a variable representing the valuation error, defined as Min (0, actual return – estimated return). This value is the difference between the actual return from the apartment sale and the return estimated by the regression model of Table 2 if this difference is negative, and zero otherwise. This 'underpricing' variable is included to control for effects related to transactions in which the seller could obtain some other utility besides financial return. For example, parents are allowed to sell their apartment to their own children for up to a 25% discount from the fair market price without tax consequences. Other possible reasons for discounts are two-apartment traps and personal bankruptcies, which can force the owners to liquidate the apartments much sooner than would be optimal.

Table 3 shows the results of a regression for the propensities to sell the apartment. There is clear evidence of loss realization aversion: the loss dummy has a negative coefficient for all three-year subperiods as well as for the whole 15-year period from 1989 to 2003. The results are statistically very strong, as evidenced by the t-values from –19 to –56.

[Insert Table 3 about here]

4.2. *Patterns in reservation prices*

Analyzing the distribution of returns more accurately can shed further light on selling behavior. Instead of considering returns from only the actual transactions, we use the hold observations with estimated prices and returns as a useful benchmark. Figure 2 shows the distributions for actual sales, as well as the hold observations dubbed ‘simulated transactions’ in the Figure. In effect, the Figure shows the returns that are actually realized, and the returns that would have been realized had the sales been randomly conducted at prevailing market prices.

For the purposes of this investigation, it is the patterns around zero return that are particularly interesting. The distribution of actual returns shows, first of all, a clear spike close to zero return. Small losses down to –7.5% are realized slightly less, compared to the frequency of opportunities to do so, and small gains of up to 10% are realized slightly more. When one moves further down the return axis to ranges of –15% to –30%, losses are again realized less. Gains of 10% to 30% are also realized less. The Figure also shows that transactions with extreme returns (< –50% or > 150%) occur more often than predicted. The discrepancy at the extremes probably reflects to a great extent prediction errors due to omitting some value relevant information in these cases.

[Insert Figure 2 about here]

To be able to use control variables, we also ran a regression similar to the one in Table 3, but with the following modification: Instead of the single loss dummy, we included dummies for returns at 2% intervals from –50% to 150%. For example, for a return of 11%, the dummy for [10%, 12%[receives the value of one, and all other dummies are set to zero. Figure 3 plots the estimated coefficient values for these return-range dummies. The Figure confirms the sudden increase in the selling probability for small gains that is apparent in the return distribution. The propensity to sell stays almost constant for positive returns up to about 25%.

[Insert Figure 3 about here]

To further study the possible patterns in reservation prices, we construct a frequency distribution of transaction returns, with fine return range categories spaced at 0.0001 intervals. Figure 4 shows the 30 most common return categories in descending order. The Figure shows that many transactions occur exactly at the prior transaction price. This is consistent with the idea that people frame the sale as a gain or loss in relation to the purchase price. Given that most sellers use an agent who charges about 4% of the transaction value, it appears that people do not consider the break-even price net of transaction costs.

In addition to zero return, returns of e.g. 50%, 25%, and 33.3% appear much more often than if selling prices were continuously distributed. Clustering is very high in the frequencies presented in the histogram, considering that of the 18,516 different return categories identified in the data, 17,398 (94%) have a frequency of 10 or less. This evidence is consistent with the idea that sellers are willing to wait longer to realize a sale price at least equal to the original purchase price, as argued by Genesove and Mayer (2001). However, as we do not have data on selling times, a formal test of this hypothesis is not possible.

[Insert Figure 4 about here]

4.3. *The impact of apartment price for loss realization*

We next examine whether loss realization aversion is weaker for wealthier apartment owners. Unfortunately, the data available for the study does not provide information about the total financial status of investors. We therefore use the total apartment price as a proxy for wealth.[2]

Table 4 shows how the propensity to sell at a loss changes between different price deciles. The variable of interest is an interaction of a loss realization dummy, and a dummy for belonging to a particular price decile. As one moves from the cheapest (1st) decile to the priciest (10th), the estimates for this interaction dummy start with a strongly negative value, then increase to zero for the third decile, and stay significantly positive and approximately constant for deciles 4 to 10. Nevertheless, the positive coefficients for interaction dummies are not so large as to eliminate loss realization aversion even among the most expensive apartments.

[Insert Table 4 about here]

Therefore, apartment price is negatively correlated with loss realization aversion, but much of the correlation is driven by the cheapest apartments. In addition to statistical significance, the effect is economically significant, as the total loss realization effect is almost twice as large in the cheapest apartment category. This result has two explanations. First, it could be that the least wealthy apartment owners more often face a binding mortgage down-payment constraint. On the other hand, it is possible that owners of pricier apartments are more sophisticated in financial decision-making.

4.4. The effect of experience and sophistication for loss realization

We also examine whether loss realization aversion is stronger for less experienced apartment owners. Behavioral biases should decrease with experience. We classify those

[2] Using price per square meter, instead of total price, generates very similar results.

sellers as experienced for whom the current apartment is not the first apartment they own. Receiving social financing to fund the apartment purchase is another potential measure of experience, or sophistication. Social financing is more common among first-time buyers: 8.2% have social financing, whereas the figure for experienced buyers is 3.3%. First-time apartment buyers receiving social financing could be the least sophisticated group.

Table 5 presents the results from regression for various combinations of the interactions among loss dummy, first-time buyer dummy and social financing dummy. The results show that loss realization aversion is not stronger for those first-time buyers who have not received social financing. This can be seen from the statistically insignificant t-value (–0.6) that the interaction variable "Loss-dummy x Inexperienced-dummy" receives. This indicates that the experience of the apartment owner does not appear to have any special impact on the propensity to sell – at least when experience is measured based on whether or not the owners are first-time apartment buyers.

[Insert Table 5 about here]

On the other hand, first-time buyers who have received social financing, do have a statistically significantly smaller propensity to sell their apartment at a loss than apartment owners in general. Buyers with social financing have lower incomes and are less wealthy. However, when the regression is run using only the social financing dummy as the inexperienced dummy, the interaction variable remains insignificant, suggesting that the result is not only due to a lower income and less wealth. One explanation is that the mortgage down payment restriction is more often binding for first-time buyers on social financing.

4.5. Loss realization in investment apartments

We finally examine whether loss realization aversion is weaker when the apartment represents a purely financial investment and is being rented. Financial investors in the apartment market might be more sophisticated than other apartment owners. Furthermore, the mortgage down payment restriction is quite rarely binding, as the equity portion in these transactions is usually much higher.

Unfortunately our data does not provide information about whether the apartment has been the primary home of the owner. We proxy the status of the apartment as a financial investment as follows. Investment apartments are usually one or two room condominiums. However, first-time buyers, who quite often buy precisely this kind of apartments, very rarely buy an investment apartment. In contrast, apartments acquired for dwelling purposes after the first apartment usually have at least two or three rooms. Social financing is also one indicator, as it is granted only for owner occupants. Therefore, a person who is not a first-time buyer *and* is buying a small condominium apartment *and* did not receive social financing is likely to be buying the apartment for investment purposes.

Regressions similar to the ones in the previous sections are conducted to study whether the propensity to sell at a loss deviates among likely investment apartments and the rest of the apartments. The results of this analysis are shown in Table 6.

[Insert Table 6 about here]

The Table shows that loss realization aversion is weaker among likely investment apartments. The Table separately shows results for one room, two room, and larger condominiums. The interaction variable between a loss-dummy and investment-dummy is statistically significantly positive for both 1 and 2 room condominium apartments. This shows that loss realization aversion is weaker in these cases. However, in the case of larger condominiums, the effect is insignificant. As we argued, these larger apartments are less likely to be bought for investment purposes.

5. Discussion

In this section we point out some links between our results and earlier findings in consumer behavior and decision-making, as well as some issues specific to the real estate market. Consumer behavior literature defines reference prices as standards against which the purchase price of the product is judged (Monroe, 1973). Note that although related, this concept is different from the prospect theory reference level. The literature on consumer behavior focuses primarily on the influence of a reference price on purchasing decisions. However, the concept of a reference price could also be fruitful in the selling and price setting decisions of individuals, as in our case. A general finding in the literature is that the most recent purchase price of an item is a strong determinant of an internal reference price when shopping again for the same goods (Dickson and Sawyer, 1990). On the other hand, additional information such as current prices of competitive products and the state of the economy, is known to be relatively more important for price expectations of durable goods (Mazumdar, Raj, and Sinha, 2005). Apartments are of course very durable goods, both in the sense of price level and purchase frequency. It is therefore interesting if internal reference prices play some role in the price expectations also for apartment markets, in addition to goods like candy bars. When updating price expectations, consumers are found to use the information of the newly encountered price only if it is sufficiently close to the prior expectation. For example, Kalwani and Yim (1992) find that consumers integrate a new price observation into their existing estimate if it falls within 4% of the regular price. The fact that we observe a clear change in the propensity to sell close to zero capital gain could suggest a similar effect: the sellers' asking price is affected by the original purchase price particularly if a realistic selling price is "close" to the purchase price.

The process of anchoring and adjustment (see Tversky and Kahneman 1974) could also play a part in the sellers' price setting behavior. Anchoring effects have been detected also in the context of real estate valuation (Northcraft and Neale 1987; Diaz and Wolverton 1998). Owners might also be inclined to overoptimism concerning the value of their apartment. For example, the owners might overstate the idiosyncratic quality component of their house, while lacking accurate information on average quality (see Taylor and Brown, 1988 for a review of research on optimism). Overoptimism combined with anchoring could result in listing the apartment exactly at the purchase price, rather than slightly below.

The observed high prevalence of apartment sales at exactly zero capital gains, and also a pronounced tendency to sell at 50% capital gains, could also be related to the psychology of round numbers. Several studies have documented the fact that consumer prices often end with the digits 0, 5, or 9 (see Schindler and Kirby, 1997). More accessible information, or in the language of Tversky and Kahneman (1973) information with high "availability", is likely to be used more frequently. According to Dehaene and Mehler (1992) numbers referred to as "round" have higher cognitive accessibility. Several studies show that the digits 5 and 10 are overrepresented in answers to various estimation tasks. The prevalence of the number 9 in retail prices, on the other hand, could be due to retailers' strategically exploiting consumers' tendency to underestimate prices ending with 9 (Schindler and Kirby, 1997). Our results suggest that these effects are also present in the price setting of apartments.

Knowledge of the original purchase price can be used strategically in the bargaining process between buyers and sellers. If the fair market value of the home is slightly below the seller's purchase price, it might pay for the seller to communicate his purchase price to potential buyers. Buyers acknowledge that it may be difficult to get a deal for less than what the previous owner paid for. If so, the original purchase price could function as a credible signal of minimum accepted value in price negotiations, even if the true minimum is lower.

6. Conclusion

We provide evidence of loss realization aversion in the greater Helsinki area apartment market. First, selling an apartment at a loss is much more unlikely than selling it at a gain. This result is not due to the positive correlation between sales volume and price levels, generally known to exist in the real estate market. Second, the likelihood of a sale occurring exactly at the purchase price is much higher than with other prices corresponding to small gains and losses. This result is consistent with psychological explanations of the loss realization aversion.

Loss realization aversion is particularly strong among low-priced apartments, and among receivers of social financing. First time sellers are not more prone to loss realization aversion after the form of financing is controlled for. Receivers of social financing have less wealth and income, so the mortgage down payment constraint might more often be binding in that group. The down payment issue is, however, probably not the only driver of loss avoidance. We show that even small losses are avoided after at least two years from purchase, when the loan to value ratio has decreased from the original even if apartment value has stayed the same. We also find strong loss realization aversion in situations where the mortgage constraint is less often binding, namely with pricier apartments, as well as apartments likely bought for investment purposes.

References

Andreassen, P., 1988. Explaining the price-volume relationship: the difference between price changes and changing prices. Organizational Behavior and Human Decision Processes 41, 371-389.

Case, K., Shiller, R., 1987. Prices of single-family homes since 1970: new indexes for four cities. New England Economic Review Sep, 45-56.

Dehaene, S., Mehler, J., 1992. Cross linguistic regularities in the frequency of number words. Cognition 43, 1-29.

Diaz, J. III, Wolverton, M.L., 1998. A longitudinal examination of the appraisal smoothing hypothesis. Real Estate Economics 26, 349-358.

Dickson, P. R., Sawyer, A. G., 1990. The price knowledge and search of supermarket shoppers. Journal of Marketing 54, 42-53.

Genesove, D., Mayer, C., 1997. Equity and time to sale in the real estate market. American Economic Review 87, 255-269.

Genesove, D., Mayer, C., 2001. Loss aversion and seller behavior: evidence from the housing market. Quarterly Journal of Economics, 1233-1260.

Goolsby, W., 1997. Assessment error in the valuation of owner-occupied housing. Journal of Real Estate Research 13, 33-45.

Grinblatt, M., Keloharju, M., 2001. What makes investors trade? Journal of Finance 56, 589-616.

Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263-291.

Kalwani, M.U., Yim, C.K., 1992. Consumer price and promotion expectations: an experimental study. Journal of Marketing Research 29, 90-100.

Kiel, K., Zabel, J., 1999. The accuracy of owner-provided house values: the 1978-1991 American housing survey. Real Estate Economics 27, 263-298.

Mazumdar, T., Raj, S.P., Sinha, I., 2005. Reference price research: review and propositions. Journal of Marketing 69, 84-102.

Monroe, K.B., 1973. Buyers' subjective perceptions of price. Journal of Marketing Research 10, 70-80.

Northcraft, G., Neale, M., 1987. Experts, amateurs, and real estate: an anchoring-and-adjustment perspective on property pricing decisions. Organizational Behavior and Human Decision Processes 39, 228−241.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775-1798.

Schindler, R.M., Kirby, P.N.,1997. Patterns of rightmost digits used in advertised prices: implications for nine-ending effects. Journal of Consumer Research 24, 192-201.

Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: theory and evidence. Journal of Finance 40, 777-790.

Statistical Yearbook of the City of Helsinki, 2004. Helsinki City Urban Facts Office. ISBN 952-473-282-3.

Stein, J., 1995. Prices and trading volume in the housing market: a model with down-payment effects. Quarterly Journal of Economics 110, 379-406.

Taylor, S.E., Brown, J.D., 1988. Illusion and well-being: a social psychological perspective on mental health. Psychological Bulletin 103, 193-210.

Thaler, R., Johnson, E., 1990. Gambling with house money and trying to break even: the effect of prior outcomes on risky choice, Management Science 36, 643-660.

Tversky, A., Kahneman, D., 1973. Availability: a heuristic for judging frequency and probability. Cognitive Psychology 5, 207-232.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science 185, 1124−1130.

Table 1

Number of transactions by year and room type

The sample period is 1987-2003.

Transaction year	Number of transactions		Number of rooms	Number of transactions	
1987-1989	61,175	19.8 %	1	75,875	24.5 %
1990-1992	51,167	16.5 %	2	108,074	34.9 %
1993-1995	43,014	13.9 %	3	70,431	22.8 %
1996-1998	47,486	15.4 %	4	40,953	13.2 %
1999-2001	52,962	17.1 %	>4	13,981	4.5 %
2002-2003	53,509	17.3 %			
Total	309,314	100.0 %		309,314	100.0 %

Table 2

Prediction model for an apartment's debt-free selling price

The table presents OLS regression results on the log of debt-free price per square meter. In addition to the variables reported, the model includes a constant term; monthly dummies for each month (except one) during the sample period 1987-2003; zip-code dummies for each postal area of Helsinki metropolitan area (except one), interacted with three time period dummies (for years 1987-1992, 1993-1998, and 1999-2003). The sample period is 1987-2003.

Continuous variables	Coefficient	t-value
Social financing-0.1475***	-49.2	
Apartment age (months)	-0.0001***	-43.4
Apartment area (m^2)	-0.0019***	-53.0
Number of rooms	-0.0239***	-25.9
Single-family house -dummy	0.2365***	100.2
Row house -dummy	0.1897***	97.8
Condominium	(omitted)	
N	186,339	
R- squared	0.852	
Adjusted R-squared	0.724	

*** statistically significant at 1%, **statistically significant at 5%.

Table 3

The propensity to sell an apartment as a function of loss indicator

The table presents OLS regression results where the dependent variable is a dummy taking the value of 1 for actual transactions, and 0 for monthly hold (no sale) decisions. The Loss -dummy obtains a value of 1 whenever the transaction price (for actual sales) or estimated price (when a sale does not occur) is below the purchase price, and 0 otherwise. Other variables in the regression model are those in Table 2, as well as Debt-per-area in EUR/m2 (except for the years 1999 and 2000 where data is not available), a dummy for first-time apartment buyers (except for years 1987 and 1990 where data is not available), and Min(0, actual return – estimated return). Column 6 uses the full sample, while columns 1-5 present results for two year subsamples.

	(1)	(2)	(3)	(4)	(5)	(6)
Loss-dummy	1989-1991	1992-1994	1995-1997	1998-2000	2001-2003	1989-2003
Coefficient	-0.006***	-0.011***	-0.004***	-0.007***	-0.015***	-0.007***
t-value	-19.4	-39.2	-21.4	-23.3	-30.2	-56.2

*** statistically significant at 1%, **statistically significant at 5%.

Table 4

The propensity to sell for a loss in various price categories

The table presents OLS regression results where the dependent variable is a dummy taking the value of 1 for actual transactions, and 0 for monthly hold (no sale) decisions. The Loss -dummy obtains a value of 1 whenever the transaction price (for actual sales) or estimated price (when a sale does not occur) is below the purchase price, and 0 otherwise. Loss-dummy decile variable represents an interaction between Loss-dummy and a dummy indicating the price decile in which the apartment belongs. For example, the 1st decile dummy obtains the value of 1 in apartment transactions that belong to the lowest decile in terms of apartment price, and zero otherwise. Deciles are determined for each year separately. Other (unreported) variables in the regression are same as in Table 3. The sample period is 1989-2003.

	Loss-dummy		Loss-dummy X decile	
Apartment price deciles	Coefficient	t-value	Coefficient	t-value
1st decile	-0.0062	-49.2***	-0.0053	-22.9***
2nd decile	-0.0068	-54.4***	-0.0005	-2.2**
3rd decile	-0.0069	-55.0***	0.0000	0.1
4th decile	-0.0069	-55.7***	0.0007	2.9***
5th decile	-0.0069	-56.0***	0.0010	4.4***
6th decile	-0.0069	-55.8***	0.0007	3.1***
7th decile	-0.0070	-56.1***	0.0012	4.8***
8th decile	-0.0069	-55.9***	0.0009	3.7***
9th decile	-0.0069	-56.0***	0.0011	4.1***
10th decile	-0.0069	-56.0***	0.0012	4.2***

*** statistically significant at 1%, **statistically significant at 5%.

Table 5

The propensity to sell for a loss and seller sophistication

The table presents OLS regression results where the dependent variable is a dummy taking the value of 1 for actual transactions, and 0 for monthly hold (no sale) decisions. The Loss -dummy obtains a value of 1 whenever the transaction price (for actual sales) or estimated price (when a sale does not occur) is below the purchase price, and 0 otherwise. The Inexperienced-dummy takes the value of one for transactions involving a first-time buyer and social financing (base case, also alternative definitions, indicated in the first column, are used in the table). Loss-dummy X Inexperienced-dummy represents the interaction between Loss-dummy and Inexperienced-dummy. Other (unreported) variables in the regression are same as in Table 3. The sample period is 1989-2003.

	Loss-dummy		Loss-dummy X Inexperienced-dummy	
Inexperienced-dummy definition	Coefficient	t-value	Coefficient	t-value
First-time buyer = YES and Social financing = YES	-0.0067***	-53.7	-0.0021***	-7.0
First-time buyer = YES and Social financing = NO	-0.0063***	-55.0	-0.0004	-0.6
Social financing = Yes	-0.0063***	-51.0	-0.0005	-1.1

*** statistically significant at 1%, **statistically significant at 5%.

Table 6

The propensity to sell for a loss for investment apartments

The table presents OLS regression results where the dependent variable is a dummy taking the value of 1 for actual transactions, and 0 for monthly hold (no sale) decisions. The Loss -dummy obtains a value of 1 whenever the transaction price (for actual sales) or estimated price (when a sale does not occur) is below the purchase price, and 0 otherwise. Investment-dummy obtains the value of 1 for apartments that are likely to be financial investments: Not a first-time buyer AND no social financing AND apartment type = condominium. The table combines these restrictions with alternative restrictions for room count, as indicated in the first column. Other (unreported) variables in the regression are same as in Table 3. The sample period is 1989-2003.

	Loss-dummy		Loss-dummy X Investment-dummy	
Number of rooms	Coefficient	t-value	Coefficient	t-value
1	-0.0066***	-49.6	0.0010***	5.5
2	-0.0067***	-50.1	0.0012***	7.8
> 2	-0.0063***	-48.6	0.0001	0.4

*** statistically significant at 1%, **statistically significant at 5%.

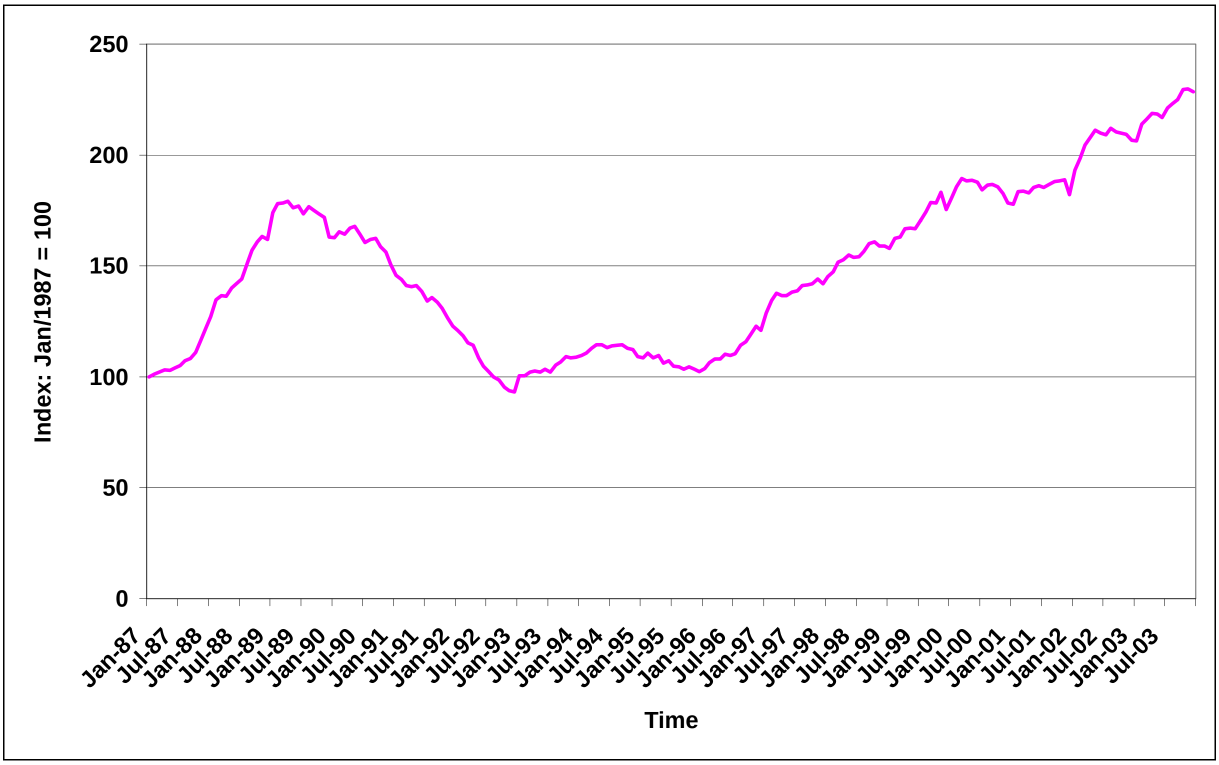

Figure 1. Hedonistic index of apartment prices in the Helsinki metropolitan area obtained from the monthly dummies of the regression model of Table 2. The sample period is 1987-2003.

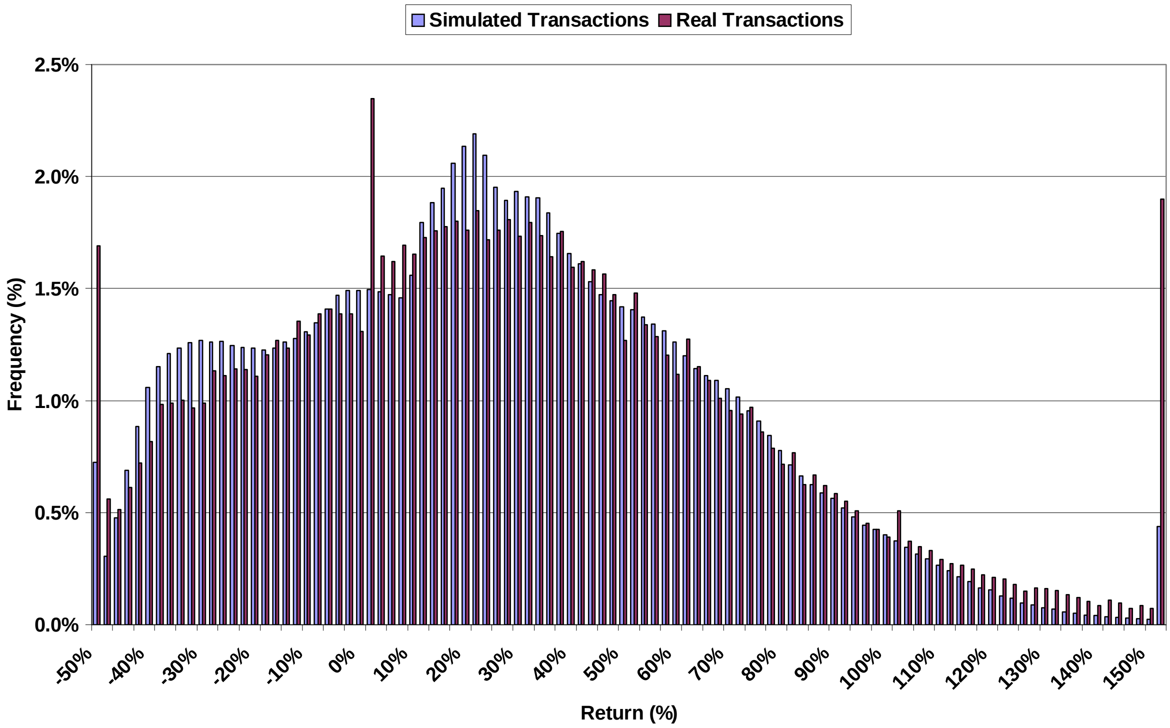

Figure 2. Frequency distribution of returns. The darker bars represent actual apartment transactions, while the lighter bars represent simulated transactions. A simulated transaction is effectively a 'no sale' observation made at monthly frequency, where the price is based on estimation as described in Section 3. Bin width of the distribution is 2.5%. The sample period is 1989-2003.

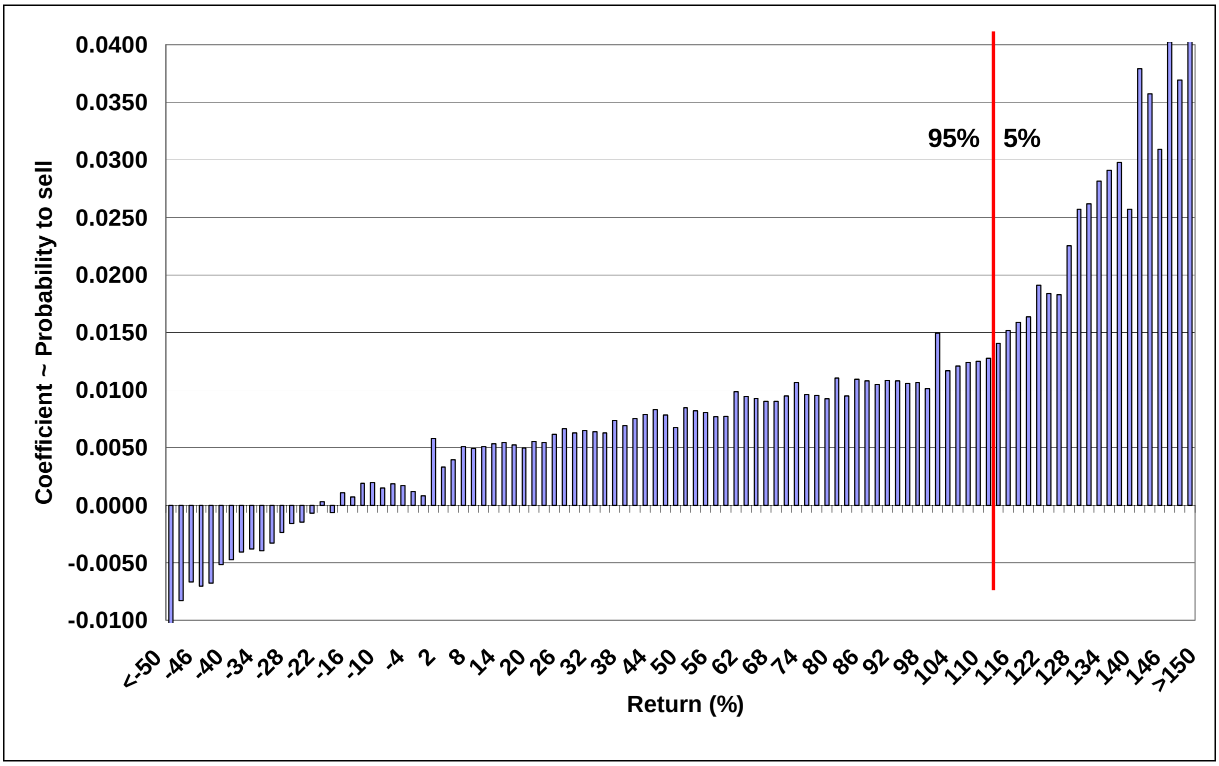

Figure 3. Probability to sell an apartment as a function of return available. The leftmost and rightmost return categories refer to returns less than -50% and greater than 150%, respectively. Otherwise, each histogram consists of a return segment that is 2 percentage points wide. The probabilities correspond to coefficients from a regression similar to that reported in Table 3, except that it includes these return categories instead of a single loss indicator. The omitted segment in the regression is [2%, 4%[. The vertical line shows the 95% percentile point of the return distribution. The sample period is 1989-2003.

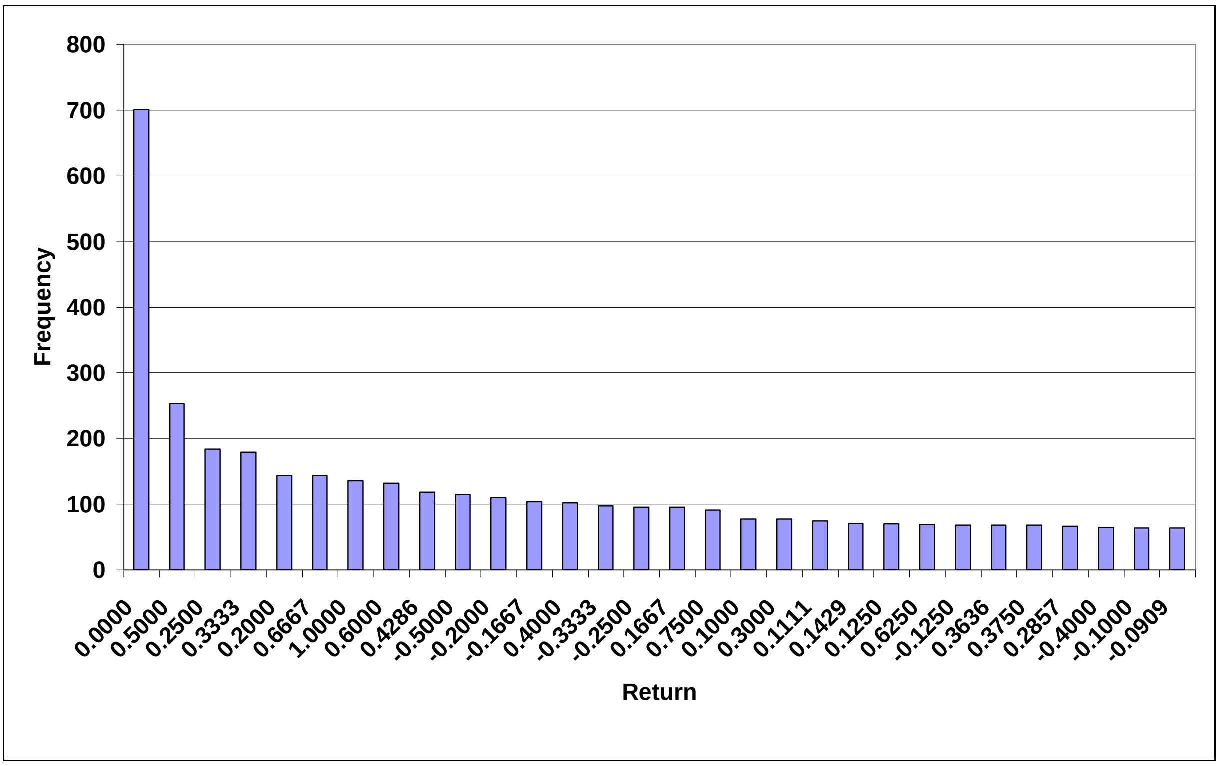

Figure 4. Frequencies of returns in actual transactions sorted in ascending order. A four-digit scale is used for separating the returns from each other. In total, 18,516 different returns were identified from 79,483 transactions. The sample period is 1989-2003.