MEAN REVERSION AND MOMENTUM: ANOTHER LOOK AT THE PRICE-VOLUME CORRELATION IN THE REAL ESTATE MARKET

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Abstract

Based on behavioral finance and economics literature, we construct a theoretical framework in which consumers of newly constructed housing units perceive prices to follow a stochastic mean reversion pattern. Given this belief and the high carrying cost maintained by real estate developers, potential buyers opt to either exercise immediately or defer the purchase. We simulate the model within a real option framework by which we show that the optimal time to wait before exercising a purchase is positively related to the price level; hence, a negative (positive) correlation between transaction volume and price level (yield) emerges. Observing data on housing prices and new construction sales in Israel for the years 1998-2007, we apply an adaptive expectation regression model to test consumers' belief in both mean reversion and momentum price patterns. The empirical evidence shows that while consumers' demand pattern is simultaneously consistent with the belief in both momentum and mean reversion processes, the effect of the latter generally dominates. Moreover, while the data does not allow for testing the volume and price-level correlation, it does provide support to the positive volume-price yield correlation.

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1 Introduction

Accumulating empirical evidence indicates a positive correlation between prices and the number of transactions in real estate markets. Stein (1995), for example, relying on US-wide volume and median real sales prices for single-family homes from 1968 to 1992, finds a highly significant positive correlation between volume and percentage change in house prices: a 10 percent drop in prices associates with a reduction in volume of over 1.6 million units.[1]

Several authors provide intuitive explanations for the positive price-volume correlation in real estate markets. On the demand side, Stein (1995) shows that for a household seeking to move to a comparable or larger house, the liquidity constraint associated with paying the down payment on the new house might become more binding if the price received for the old house has dropped.[2]

On the supply side, Cauley and Pavlov (2002) show that during price downturns, the net value of the option to sell may exceed its net carrying cost when the amount of equity in the property is limited, thus motivating the owner to optimally maintain the option alive. Cornell et al. (1996) argue that the decline in transaction volume that accompanies a drop in market prices might also be explained by the "lock-in" effect that is caused by the valuable option to default on a mortgage. Krainer (2001) argues that when real estate rental markets do not exist and market prices are relatively high, the opportunity cost of maintaining an empty housing unit combined with the probable future price decline motivates the seller to rapidly compromise on the price. Likewise, the comparatively high value of housing services that accompany relatively high market prices motivates buyers to quickly reach a closing.[3]

The common denominator to the studies mentioned above is that they all rely on traditional rational economic assumptions in order to explain the commonly detected positive price-volume correlation in the housing market. In contrast to this thread of

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[1] This evidence stands in contrast to the efficient market and rational expectation theory [see, among others, Lucas (1978), Case and Shiller (1989) and Poterba et al. (1991)]. For further empirical documentation of the positive price-volume correlation in real estate markets, see, among others, Ortalo-Magne and Rady (1998), Leung et al. (2002), and Chu and Sing (2005).

[2] This explanation, which is empirically supported by Genesove and Mayer (1997), may hold, of course, only if the illiquidity constraint is sufficiently substantial in the market.

literature, Genesove and Mayer (2001) propose an explanation for the price-volume correlation that is neither motivated by liquidity constraints nor dependent on the amount of equity retained in the asset. Instead, they present empirical evidence for the presence of loss aversion behavior on the part of potential sellers in the residential real estate market. This "irrational" behavior, according to the authors, may explain properties' longer time on the market as well as the drop in the frequency of transactions in depressed markets.[4]

In this research, we continue the general approach of Genesove and Mayer (2001) as we theoretically propose and empirically test a diversion from the traditional rational assumption in studying the price-volume correlation in real estate markets. Both our proposed theory and the empirical framework that follows differ from that of Genesove and Mayer (2001). Specifically, in the model, consumers act under the perception that prices follow a (stochastic) mean reverting process.[5] They encounter real estate developers whose inventory cost is high and who are, thus, always willing to sell at the current market price.[6] Based on a real-option modeling, we solve the mean stopping time (i.e., the expected optimal time to wait before exercising a purchase) by conducting a simulation along the lines of the method proposed by Longstaff and Schwartz (2001). This allows us to examine the optimal time of purchase vis-à-vis the perceived mean reverting price pattern.

We find that the optimal stopping time rises with the price; hence, a negative correlation between transaction volume and price level emerges in the housing for new construction. However, that correlation, in conjunction with the perceived mean reversion process, produces a positive correlation between transaction volume and price yield. We

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[3] Also see the asymmetric information motivation for the positive price-volume correlation in Berkovec and Goodman (1996).

[4] For more on loss aversion and prospect theory, see Kahneman and Tversky (1979).

[5] The long-term mean price may of course either be constant or experience a drift (see further details in the empirical section).

[6] In our model, potential consumers face developers as those, unlike potential sellers in the secondary market, face substantial carrying costs and, thus, are generally willing to sell their housing stock at the current market price. In contrast, sellers of second-hand assets generally maintain the same level of flexibility (to either rush or delay the transaction) as that of buyers and may thus choose to delay (rush) the sale if the current price terms favor the buyers (sellers), given the belief in the mean reverting price process. This zero-sum game situation between buyers and sellers in the secondary market limits the applicability of our theory to the market segment of new housing units.

further generate predictions with respect to the relation between the optimal stopping time and the distance of the price from its long-term mean, the speed of convergence to the mean, and the price volatility.

Furthermore, observing the monthly time series of the housing price index and sales of new construction units in Israel from January 1998 to June 2007 (earlier data on sales is unavailable), we extend the geometrical-lag model of adaptive expectations to empirically test the prevalence of consumers' belief in (and action upon) mean reversion and momentum price patterns in the new construction segment of the housing market.[7]

Unfortunately, because the time series of both price level and the transaction volume show significant unit-root results, we may not directly test for their correlation. Nonetheless, focusing on the price yield (as opposed to the price level), we find that when prices are below (above) their long-run mean and exhibit a recent positive (negative) momentum, transaction volume significantly increases (decreases); hence, we have empirical support of the positive correlation between price yield and volume in the housing market of new construction. Moreover, we find that when prices are below (above) their long-term mean and yet experience a recent negative (positive) momentum—that is, when mean reversion and momentum price patterns lead to contradicting price expectations—transaction volume yet rises (drops), although, more moderately. This, in turn, implies that while consumers' demand is affected by the perception of both mean reversion and momentum price patterns, the former effect apparently dominates.

In the next section we present a brief overview of the relevant finance and real estate literature on price momentums and mean reversion. In Section 3 we present the theoretical framework and the simulation. We present the empirical model and the resulted evidence in Section 4. We summarize in Section 5.

2 Literature Review

[7] For adaptive expectations and geometrical-lag models, see, for example, Kmenta (1997) and Greene (2003). To the best of our knowledge, the geometrical-lag model has never been previously applied in this context.

Following Kahneman and Tversky (1982, 1986), we assume that "the predicted value (price) is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impression" [Kahneman and Tversky (1982, p. 416)]. Accordingly, buyers in the model adjust their expectations regarding future market prices under the representative bias [see Kahneman and Tversky (1974)]; namely, buyers tend to ignore simple probability rules and, instead, view an event as a representative of a phenomenon. Particularly, in the context of our study, buyers tend to, on one hand, over-weigh the recent price trend and, on the other hand, act under the perception that prices follow a mean reversion pattern.[8]

There is extensive empirical, theoretical, and experimental finance literature on the various manifestations of the representativeness heuristic within the context of investments and capital markets. Keim and Madhavan (1995) document the presence of momentum trading by institutional investors. Bange (2000), using small investors survey data, documents the prevalence of positive feedback trading.[9] Dhar and Kumar (2001), investigating trading of individual investors in the U.S., further document the existence of momentum-type investors on both the buy and sell ends. Choe et al. (1999) find momentum trading strategy among foreign investors in Korea, and Grinblatt and Keloharju (2001) show that sophisticated foreign investors in Finland also tend to act as momentum traders. Bauman et al. (1999) find that investors and research analysts in 22 countries outside the U.S. tend to assume that past growth rates in earnings-per-share will continue into the future. Empirical evidence on the mean reversion price pattern of assets includes, among others, Campbell and Shiller (1988), Lo and Mackinlay (1988), Fama and French (1988), Poterba and Summers (1988), Balvers et al. (2000), and Chen and

[8] Representativeness is further related to the recency bias and the "hot hand" effect, i.e., the expectation for the prevalence of the recent trend [see, Gilovich et al. (1985)]. The latter implies that people may detect price patterns even when prices do, in fact, follow a random walk. DeBondt and Thaler (1985) argue that, by violating basic statistical rules, the representativeness heuristic may lead to price over-reaction, that is, people's expectation for positive autocorrelation in price patterns. Also, note that the representativeness heuristic further includes the frequency bias; the tendency to judge predictive relationships according to frequency as opposed to relative frequency [see, for example, Tversky and Kahneman (1973) and Estes (1976)].

[9] Momentum trading and positive feedback trading are interchangeably used to term the trend-chasing trading strategy.

Sauer (1997) for stocks, and Frankel and Rose (1995), and Chen and Jeon (1998) for currency.[10]

Theoretical literature on price momentum that is based on investor cognitive biases is also widespread. For example, relying on investor expectations formed on the basis of representativeness and, particularly, on the law of small numbers, Barberis et al. (1998) show that even if actual prices follow a random walk, momentum price patterns may prevail. Also, relying on representativeness and the law of small numbers, DeLong et al. (1990) model the positive feedback trading, that is, investors' empirically observed strategy to buy more of an asset which has recently increased in value. Based on the self-serving attribution bias, Daniel et al. (1998) show the persistence of price momentum in the market, and Odean (1998) shows that the latter may be the result of overconfidence.[11] In addition, recent literature in behavioral finance shows that a mean reversion price pattern may result due to investors' irrational behavior. Barberis and Huang (2001) and Barberis et al. (2001), for example, show that loss aversion may produce mean reversion in individual stock returns. Also, Barberis et al. (1998) show that representativeness and conservatism may further result in mean reverting prices.[12] Finally, Daniel et al. (1998) use investor overconfidence and biased self-attribution to once again generate mean-reverting returns.

Experimental finance further documents evidence for trend-chasing strategies [see, for example, Andreassen and Kraus (1990) and DeBondt (1993)]. DeBondt (1993) for example, shows that the expectation for continuing upward (downward) price trend in bullish (bearish) markets is particularly prevalent among individual investors.

Within the real estate economics literature, evidence on non-random price patterns includes Case and Shiller (1989), who report that a change in real housing prices in a given year tends to predict a change in the same direction, one-quarter to one-half as

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[10] While some of these studies use a variance-ratio test, others apply the *habit persistence* model. As will be clarified later, we are not interested in directly testing for the prevalence of momentum and mean reversion price patterns but rather in exploring whether the transactions are based on consumers' belief regarding these patterns. We thus apply the adaptive expectation model (see the next section). On the differences and similarities between the models see, for example, the discussion in Kmenta (1997).

[11] The self-serving attribution bias is one's tendency to attribute good outcomes to own skills and bad outcomes to the luck of the draw [see, for example, Forsyth and Schlenker (1977)] Also, on the modeling of over-reaction, under-reaction, and momentums, also see Hong and Stein (1999).

[12] Conservatism is the tendency of individuals to slowly adjust to new information.

large in magnitude, in the following year. Further evidence of either positive or negative price autocorrelations in real estate prices appears in, for example, Hamilton and Schwab (1985), Linneman (1986), Cutler et al. (1991), Hosios and Pesando (1991), Ito and Hirono (1993), Kuo (1996), Stevenson (2002), Liow (2003), and Hwang and Quigley (2004).[13]

With respect to momentum trading in real estate, Mei and Saunders (1997) find that commercial banks and savings and loans' real estate investments are effectively employed under a trend-chasing strategy, that is, real estate investments are increased (decreased) when *ex ante* returns on real estate are below (above) their mean levels. Ling (2005) shows that investment strategies of commercial real estate experts (represented by Real Estate Research Corporation survey) are "akin to driving a car by looking in the rear view mirror" [Ling (2005), p. 149]. In other words, commercial real estate investors over-weigh recent returns and under-weigh long-term averages in conducting their real estate investments.[14]

Finally, Linneman (1986) is the first to study and report evidence on mean reversion in real estate prices. More recently, by examining a large dataset of dwellings sold in Sweden, Hwang and Quigley (2004) find evidence that individual house prices follow a mean reversion process and Liow (2003) finds evidence of mean reversion by observing property stock prices in Singapore [also see Guntermann and Smith (1987) and Cutler et al. (1991)].

3 Model and Simulation

Consider a real estate market where developers offer their stock of housing assets to prospective first-time home buyers. Because developers face a substantial carrying cost, they are always willing to supply their housing stock at the given market price.[15]

[13] Note that, in contrast to shares of common stock, autocorrelation in real estate prices in the short run does not immediately imply an arbitrage opportunity since there is no direct market in which one may short-sale real estate assets.

[14] For more on buyers' irrational beliefs in the real estate market, see, for example, Case and Shiller (1988) and Ben-Shahar (2007).

[15] First-time home buyers, rather than repeat buyers, are considered in the model as the former are not likely to maintain a hedge on the amount invested in the real estate asset. The model may also include repeat buyers as long as the price correlations among the segments of the real estate market are low. Also, note that the carrying costs borne by the developers specifically include substantial financing cost.

At any period t, t=0,1,…,T, a prospective buyer observes the price for the demanded asset, denoted by x_t. The buyer then expects the price, x_t, to follow a stochastic mean reversion process. In particular, the buyer supposes that the evolution of the price follows the stochastic process[16]

(1)

$$dx_t = \gamma(\ln \bar{x} - \ln x_t)x_t dt + \sigma x_t dW_t,$$

where $\{W_t, t \geq 0\}$ is a Wiener process, $W_0=0$, and $\bar{x}$, γ, and σ are positive constants. This process converges to the long-term mean price $\bar{x}$ at a momentum speed γ, with an instantaneous standard deviation σ for a given initial condition x_0. Note that Equation (1) exhibits the realistic feature according to which the price, x_t, cannot attain a negative value and, further, both the diffusion and the drift are positively monotone in the price.[17]

At any period t, the potential buyer confronts the price offer, x_t [drawn from the price process in Equation (1)]. He or she then decides whether to exercise the purchase or defer it to the next period. By choosing to wait an additional period, however, one waives the right to purchase at the current price. In addition, one incurs further net carrying cost (or gains the net return on the alternative investment) at a rate of r. In return, one maintains the option to purchase the housing asset (or a comparable unit) at a future period and potentially close a better deal.

Hence, at any time t, t=1,…,T-1, the potential buyer optimizes the following objective

(2)

$$p_t = \min[x_t, E_t(p_{t+1})e^{-r}],$$

where, p_t is the value to be optimally paid for the asset given the option to defer the purchase to the next period and E_t is the expectation operator given the time t information

However, they may further include maintenance cost, guarding and supervision cost, etc. In contrast, the carrying cost on the part of buyers is mainly the alternative rental cost.

[16] Expiration date is exogenous in the model. Realistically, one can view T as the final period in which the buyer must purchase the property for an idiosyncratic cause such as an expected change in the size of the household (due to marriage, divorce, new-born child, etc.) or any other exogenous event that induces the purchase.

[17] For more on similar processes, see Schwartz (1997), for example. Also, note that we focus on a partial equilibrium established in the short run. We do not consider the long-run equilibrium in which price reversals may occur. For the latter, see, for example, Barberis et al. (1998) and DeLong et al. (1990).

set. That is, at any period t, the buyer minimizes the cost to be paid for the asset by opting for the lower between the current price and the present value of the expected next period price under the perception that prices follow the process in Equation (1). The terminal condition under which the buyer may select the best deal is

(3)

$$p_T = x_T$$

The path-dependence of the price process in Equations (1) somewhat limits the set of plausible procedures for computing the optimal period for exercising the purchase of the asset, t^* (henceforth, the optimal stopping time). We use the least squares valuation procedure suggested by Longstaff and Schwartz (2001), the advantage of which is that it can be used for solving the optimal stopping time of complex (path-dependent) derivatives.

The stochastic price process in Equation (1) may be simulated from the following equation:

(4)

$$x_t = \bar{x} \exp\{[-e^{-\gamma\Delta t} \sigma\varepsilon + e^{-\gamma\Delta t} \ln(x_{t-1} / \bar{x})\gamma + \sigma\varepsilon] / \gamma\},$$

where $\varepsilon \sim N(0,1)$.[18] Given the price process in (4), we may now numerically solve for t^*. The steps of the simulation along the lines of Longstaff and Schwartz (2001) are shown in the appendix. We first focus on the sensitivity of the optimal stopping time t^* to changes in the initial price x_0. Following Figures 1 and 2 (see appendix), we argue

Proposition 1: *The optimal stopping time rises with the price, ceteris paribus.*

Corollary 1: *The correlation between the price level and transaction volume is negative.*

Corollary 2: *The correlation between the price yield and transaction volume is positive.*

The intuition is immediate: Due to mean reversion in the price process, when x_0 falls below its long-term mean $\bar{x}$, it tends (more often than not) to increase. At the same

[18] Equation (4) is the solution to the differential equation in (1), derived by using Maple software package.

time, potential buyers, in anticipation for a higher future price, rush the purchase. Hence, transaction volume is large when prices are below their long-term mean and a negative price level and volume correlation emerges. In contrast, when x_0 is above its long-term mean, it is more likely to drop than it is to continue to rise. This time, expecting prices to drop, potential buyers tend to defer the purchase. The relatively high prices and the deferred purchases, however, once again produce the negative price-level and volume correlation.

Moreover, Proposition 1 combined with the mean reversion price process [represented in Equations (1) and (4)] generate a positive correlation between transaction volume and the price yield: When prices are below their long-mean, the average price yield is positive (as prices are more likely to increase) while the volume at the same time is relatively high. In contrast, when prices are above their long-term mean, they tend to drop and, thus, the resulted average price yield is negative. This occurs, however, when transaction volume is relatively low. Hence, a positive price yield and volume correlation arises.

Further focusing on Figure 1, we argue

Proposition 2: *For a price above its long-term mean, the optimal stopping time drops with the standard deviation of the price process.*

Proposition 3: *For a price at or below its long-term mean, the optimal stopping time is generally independent of the standard deviation of the price process.*

That is, when the initial price is at or below its long-term mean, the buyer simply capitalizes on the opportunity to purchase at the current price (which is below or at its long-term mean) before prices rise. In contrast, when the price is above its long-term mean, a lower standard deviation associates with a longer time period until prices considerably drop and, thus, the optimal stopping time tends to rise. Hence, the greater the standard deviation of the price process is, the less sensitive becomes the optimal stopping time to the price level.

Finally, following Figure 2 in the appendix, we argue

Proposition 4: *For a price above its long-term mean, the optimal stopping time drops with the speed of convergence to the long-term mean price.*

Proposition 5: *For a price at or below its long-term mean, the optimal stopping time is generally independent of the speed of convergence to the long-term mean price.*

Intuitively, when prices are relatively high and expected to drop relatively rapidly toward the long-term mean price, potential buyers do not expect to wait long before they exercise the transaction at a lower price. In contrast, if the duration of the price drop toward the its long-term mean extends (i.e., when the speed of convergence is relatively low), buyers tend to be more patient and wait longer before they choose to optimally exercise the purchase. When prices are below (at) their long-term mean, however, they are likely to increase (maintain) and thus, independently of the speed of convergence, there is no rational reason on the part of potential buyers to defer the purchase.

4 Empirical Test

We empirically examine and extend the framework of the theoretical section. Our main objective is to test whether buyers in the market for new construction act under the perceived mean reversion price pattern. We further extend the framework to test for the persistence of consumers' concurrent belief in price momentum. For conducting our test, we extend the geometrical-lag model methodology.[19] We then apply the proposed methodology to Israeli housing market data, where we observe the monthly time series of the housing price index and sales of new construction from January 1998 to December 2007.[20]

We propose a methodology for testing for the presence of the belief in mean reversion and momentum price patterns using the difference form of the transaction

[19] See, for example, Kmenta (1997).
[20] The data is available from the Central Statistics Bureau in Israel (www.cbs.gov.il/reader/?MIval=cw_usr_view_Folder&ID=141).

volume and prices index series.[21] Suppose that the natural logarithm of the number of transactions of new units in period t (denoted by Y_t) is determined by the expected natural logarithm of the housing price in the next period (X^*_{t+1}) and a time trend measured by the index t. This relationship may be expressed as

(5)

$$Y_t = \delta + \alpha t + \beta X^*_{t+1} + \varepsilon_t ,$$

where α, β, and δ are parameters and ε_t is a stochastic random disturbance term.

A more convenient way to write Equation (5) is in difference form. Lagging Equation (5) by k periods and subtracting the result from (5) yields

(5a)

$$\Delta_k Y_t = \alpha k + \beta \Delta_k X^*_{t+1} + \Delta_k \varepsilon_t ,$$

where $\Delta_k Y_t = Y_t - Y_{t-k}$ and $\Delta_k X^*_{t+1} = X^*_{t+1} - X^*_{t+1-k}$ — reflecting the yield over k periods, and $\Delta_k \varepsilon_t = \varepsilon_t - \varepsilon_{t-k}$.[22]

As the expected price in period t+1, X^*_{t+1}, is unobservable, estimation of Equations (5) and (5a) in their current form is impossible. We thus use the following specification:[23]

(6)

$$X^*_{t+1} = (1-\lambda) X_t + \lambda X^*_t ,$$

where λ, $0 \le \lambda \le 1$, is a parameter. We may further express Equation (6) in a difference form:

(6a)

$$\Delta_k X^*_{t+1} = (1-\lambda) \Delta_k X_t - \lambda \Delta_k X^*_t ,$$

where $\Delta_k X_t = X_t - X_{t-k}$.

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[21] Our tests show that both series (price levels and transaction volume) display a random-walk pattern. In order to encompass the limitations imposed by the presence of a unit root in our time series data, we transform the series into a difference form for which the unit-root hypothesis is generally rejected. The results of the unit root tests may be received from the authors upon request.

[22] These returns could be computed in either nominal or real terms as well as in terms of premium over the return on the risk-free asset. Genesove and Mayer (2001), for example, provide evidence that supports the nominal terms approach, which we later assume for our test.

The specification in (6) and (6a) implies that the expected natural logarithm of the housing price level in period t+1 (X^*_{t+1}) is determined using a weighted average of the current natural logarithm of the housing price level (X_t) and the expected natural logarithm of the price in period t (X^*_t). The weight, given by the parameter λ, draws an important distinction between two extreme cases: (a) $\lambda = 0$, implying a purely rational behavior in an efficient market, i.e., consumers form their expectation of future prices based on the current price as the latter incorporates all available information; (b) $\lambda = 1$, implying that, in forming their price expectations, consumers merely consider their past expectations and ignore any information that might be reflected in the current price.

Note that both $\lambda = 0$ and $\lambda = 1$ are inconsistent with consumers' belief of mean reversion and momentum price patterns. Our first empirical task is, therefore, to estimate λ to guarantee that the condition $0 < \lambda < 1$ is statistically maintained (the results are presented below).

Solving Equation (6a) recursively (with infinite substitutions) yields[24]

(7)

$$\Delta_k X^*_{t+1} = (1-\lambda)(\Delta_k X_t + \lambda \Delta_k X_{t-1} + \lambda^2 \Delta_k X_{t-2} + \cdots),$$

and substituting (7) into (5a) produces[25]

(8a)

$$\Delta_k Y_t = \alpha k + \beta(1-\lambda)(\Delta_k X_t + \lambda \Delta_k X_{t-1} + \lambda^2 \Delta_k X_{t-2} + \cdots) + \Delta_k \varepsilon_t .$$

Following Klein (1958), Dhrymes (1969), and Zelner (1970), we may estimate the parameters in Equation (8a) by the following method. We divide the series on the right-hand side of (8a) into two parts, finite and infinite, such that

(8b)

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[23] This specification is referred to as *adaptive expectation* model as the expectations are constantly modified with the new coming information [see Kmenta (1997)].

[24] Note that if $0 \le \lambda < 1$, then the term $\lambda^\infty \Delta_k X^*_{t-\infty}$, which approaches zero, could be omitted.

[25] Note that the equation derived in (8a) is, in fact, similar to a VAR model with infinite lags. Unlike the VAR model, however, (8a) includes the current return, $\Delta_k X_t$ and, therefore, when λ=0, the coefficient β directly estimates the correlation between $\Delta_k Y_t$ and $\Delta_k X_t$. Furthermore, (8a) does not contain lagged dependent variables on the right-hand side and thus we avoid the problem of biased estimators in small samples [see, for example, Ramanathan, (2002)].

$$\Delta_k Y_t = \alpha k + \beta(1-\lambda)(\Delta_k X_t + \lambda\Delta_k X_{t-1} + \lambda^2\Delta_k X_{t-2} + \cdots + \lambda^{t-1}\Delta_k X_1)$$
$$+ \beta(1-\lambda)\lambda^t(\Delta_k X_0 + \lambda\Delta_k X_{-1} + \lambda^2\Delta_k X_{-2} + \cdots) + \Delta\varepsilon_t .$$

For the infinite expression on the right-hand side of (8b), the following equality holds:

(9)

$$E(\Delta_k Y_0) - \alpha k = \beta(1-\lambda)(\Delta_k X_0 + \lambda\Delta_k X_{-1} + \lambda^2\Delta_k X_{-2} + \cdots),$$

where $E(\cdot)$ is the expectation operator. Hence, Equation (8b) may, in turn, be expressed as

(8c)

$$\Delta_k Y_t = \alpha k + \beta(1-\lambda)\Delta_k W_t^{(\lambda)} + (\theta - \alpha k)\lambda^t + \Delta_k \varepsilon_t ,$$

where $\Delta_k W_t^{(\lambda)} = \Delta_k X_t + \lambda\Delta_k X_{t-1} + \lambda^2\Delta_k X_{t-2} + \cdots + \lambda^{t-1}\Delta_k X_1$ and $\theta = E(\Delta_k Y_0)$.

The parameters α, β, λ, and θ can now be jointly estimated from equation (8c) by a Full Information Maximum Likelihood (FIML) procedure. The FIML function may be expressed by the following equation:

$$L = \frac{1}{2}\log(1-\rho^2) - \frac{n}{2}\log(2\pi\sigma_\varepsilon^2) - \frac{\sum \Delta_k \varepsilon_t^2}{2\sigma_\varepsilon^2},$$

where ρ represents the first order serial correlation, n is the number of observations, $\sigma_\varepsilon^2 = \sigma^2 / (1-\rho^2)$, and σ^2 is the variance of the random disturbance term.

We observe the monthly time series of the housing price index and sales of new housing construction in the years 1998-2007 in Israel. Tables 1a and 1b in the appendix present the estimated weight ($\hat{\lambda}$) given current and k-months lag price information ($k = 2,\ldots,6$) and the estimated serial correlation ($\hat{\rho}$). Each lag represents the nominal return on the housing price index over k months. The main objective of the tables is to report the calculated statistics for testing the hypotheses that $\lambda = 0$ and $\lambda = 1$.

Table 1a (1b) reports the outcomes under the case that the restriction $\rho = 0$ is imposed (not imposed). As one can see, the evidence suggests that $\hat{\lambda}$ falls within the range 0.85-0.9 and is highly significant under the null $\lambda = 0$, which is therefore rejected. The evidence thus indicates that a higher (smaller) weight is given to historical (current) prices. Yet the hypothesis $\lambda = 1$ is also rejected in most cases. The t-statistic under the null $\lambda = 1$ for lags 2-6 (3-6) is between -3.67 and -1.77 (-15.71 and -1.66) when serial correlation is ignored (considered). Hence, the outcome cannot reject the assumption that consumers exercise the transactions under the belief in mean reversion and momentum price patterns. Yet, that $\hat{\lambda}$ is relatively high might suggest that consumers are relatively slow to respond to new information associated with prices in the housing market.

Our next task is to directly test for the prevalence of consumers' belief of mean reversion and momentum price patterns. We first compute the perceived long-term mean price. We posit that at every period *t*, potential buyers adjust their perceived long-term mean price by computing the long-run trend line (representing the dynamic long-term mean price) given the available information (prices) up to time *t*. The perceived long-term mean price at time *t* is thus computed from the following equation:

(9)

$$x_t = \delta_0 + \delta_1 t + u_t ,$$

where $x_t = \exp(X_t)$ (that is, x_t is the housing price level at time *t*), δ_0, and δ_1 are parameters, u_t is a random disturbance term, and *t* represents monthly periods. We re-estimate Equation (9) for every *t* (thereby allowing the long-run price trend to adjust over time) from which we then compute

(10)

$$\hat{x}_t = \delta_0 + \delta_1 t .$$

We interpret and consider the projected value $\hat{x}_t$ as the perceived long-term mean price at period *t*.[26] For testing consumers' belief in mean reversion and momentum price behavior, we should now define two dummy variables: *BM* is a dummy variable that receives 1 if the time *t* housing price level x_t is below the long-term mean price at time *t*, $\hat{x}_t$, and is 0 otherwise; and *NEG* is a dummy variable that receives 1 if the time *t* return on the housing price index is negative and is 0 otherwise.

[26] In order to estimate Equation (9) we must require that $t \geq 3$; otherwise, the degrees of freedom do not suffice for the estimation of the model. We therefore add additional observation of the housing price index for the last two months of the year 1997. Also, note that the procedure that is suggested in (9) and (10) potentially allows the perceived long-term mean price to be non-constant (i.e., to experience either a positive or a negative trend).

Given the dummy variables *BM* and *NEG*, we may substitute the parameters α, β, and θ in Equation (8c) with the following:

(11a)

$$\alpha = \alpha_0 + \alpha_1 BM + \alpha_2 NEG + \alpha_3 BM \times NEG,$$

(11b)

$$\beta = \beta_0 + \beta_1 BM + \beta_2 NEG + \beta_3 BM \times NEG,$$

and

(11c)

$$\theta = \theta_0 + \theta_1 BM + \theta_2 NEG + \theta_3 BM \times NEG.$$

Note that, given the estimated Equation (8c) and the definition in (11b), it is the coefficient β by which we can now distinguish between consumers' belief in mean reversion and momentum price patterns. That is, following (11b), four potential categories emerge:

(1) $NEG = BM = 0$ [the base category, i.e., following (11b), $\beta = \beta_0$], that is., the time *t* price return is *positive* while the price is *above* its long-term mean;

(2) $NEG = 0$ and $BM = 1$, i.e., the time *t* price return is *positive* while the price is *below* its long-term mean (that is., $\beta = \beta_0 + \beta_1$);

(3) $NEG = 1$ and $BM = 0$, i.e., the time *t* price return is *negative* while the price is *above* its long-term mean (that is, $\beta = \beta_0 + \beta_2$); and

(4) $NEG = BM = 1$, i.e., the time *t* price return is *negative* while the price is *below* its long-term mean (that is, $\beta = \beta_0 + \beta_1 + \beta_2 + \beta_3$).

Following the above formulation, the momentum and mean reversion patterns affect prices in the same direction under categories (2) and (3). Under category (2) both patterns tend to raise the price, while under category (3) both patterns tend decrease the price. Hence, as the coefficient β represents the marginal correlation between the current percent change in the number of transactions and the current price return [see Equation (8c)], we expect, following (11b), that both $\beta_0 + \beta_1$ and $\beta_0 + \beta_2$ are positive. In contrast, under categories (1) and (4), the two patterns (momentum and mean reversion) affect the price in opposite directions; hence, we expect both β_0 and $\beta_0 + \beta_1 + \beta_2 + \beta_3$ to be smaller (either negative, zero, or positive depending on which effect is more dominant) than $\beta_0 + \beta_1$ and $\beta_0 + \beta_2$, respectively.

Table 2 in the appendix presents the results from the estimation of Equation (8c). Particularly, we focus on the estimated value for β under the four categories. We re-estimate (8c) for lags $k = 2,\ldots,6$ (k representing months). First, note that, in general, the estimated coefficient for β is in line with consumers' belief in both mean reversion and momentum price patterns. For all categories (1)-(4) and for all lags, the sign on β is in line with our predictions, i.e., positive under categories (2) and (3) and negative (that is, smaller) under categories (1) and (4) (only $\hat{\beta}_0$ is insignificant for k=2,3 and $\hat{\beta}_2$ is insignificant for k=2,5, although they maintain the expected signs). This produces a support to the assertion that transactions are based on consumers' belief in both momentum and mean reverting price patterns.[27]

Moreover, the estimated β for categories (2) and (3) is generally positive (implying a positive correlation between the current price trend and the current change in transaction volume) while the estimated β for categories (1) and (4) is generally negative (implying a negative correlation between the current price trend and the current change in transaction volume). In other words, our empirical evidence suggests a refinement to the empirical literature on the price-volume correlation,[28] namely, that in the market for new housing units, if prices are above (below) their long-term mean and recently experienced a negative (positive) trend, then the correlation between the price yield and the percent change in transaction volume is positive. If, however, prices are above (below) their long-term mean and recently experienced a positive (negative) trend, then the examined price-volume correlation is negative.

In order to test for the significance of the sign of β under each of the four categories, we further generate a confidence interval at a 95% significance level for the

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[27] In most cases the estimated λ in Table 2 are different from the corresponding estimates obtained in Table 1. In fact, substitution of the λ obtained from Table 1 as an initial value yields a local maximum. This might be the outcome of the high multi-colinearity between $\Delta_k x_t$ and the dummy variable *NEG* with $R^2 = 0.59$.

[28] See, for example, Stein (1995), Ortalo-Magne and Rady (1998), Leung et al. (2002), and Chu and Sing (2005).

estimated β for categories (1)-(4). Note that in 17 out of the 20 estimated cases (four different categories multiplied by five different lags) the entire interval maintains the sign (either negative or positive) of the estimated coefficient.[29]

The evidence suggests that the effect of the perceived mean reversion price pattern generally dominates that of the price momentum in consumers' decision-making regarding the exercise of the purchase. That is, under category (1), for example, the price experiences a time *t* positive return (and is thus expected to continue to rise at time *t*+1 according to the momentum belief) while, at the same time, it is above the long-term mean price (and is, therefore, expected to drop at *t*+1 given the mean reversion belief). The negative sign on the coefficient β in this case (implying smaller transaction volume) supports the notion that consumers expect that prices will drop in the foreseeable future (and thus volume diminishes), i.e., the mean reversion effect overpowers that of the price momentum.

Finally, note that the decreasing transaction volume that appears when prices are above their long-term mean [under categories (1) and (3)] and the increasing volume that prevails when prices are below their long-term mean provide further support to the negative correlation between the price level and transaction volume in the newly constructed unit segment of the market.

5 Summary

Considering a real estate market with developers on the supply side and first-time home-buyers on the demand side, we construct a real option framework where the stochastic price process of the assets is mean reverting and by which we provide a simple and intuitive rationale for the correlation between the price yield and the transaction volume in the real estate market. Essentially, given their anticipation for a stochastic mean reversion price process, potential buyers tend to maintain the option to purchase alive the

[29] We generate the confidence interval for category (2) in the following way: We define a new parameter ψ_2 for category (2) such that $\beta_0 + \beta_1 = \psi_2$. We then substitute $\beta_1 = \psi_2 - \beta_1$ into Equation (11b) yielding (11b*)

$$\beta = \beta_0 (1 - BM) + \psi_2 BM + \beta_2 MINUS + \beta_3 BM \times MINUS \, .$$

higher is the price above its long-term mean (implying that a negative price trend is more likely) and tend to exercise the option when the price is below its long-term mean (when prices experience a positive return on average). Our model further provides a series of predictions regarding the effect of price volatility and the speed of price convergence to its long-term mean on the optimal time of purchase.

We further conduct an empirical test based on the monthly time series of the housing price index and the sales of new construction in Israel from January 1998 to June 2007. We extend the geometrical lag model of adaptive expectations by which we present evidence for consumer demand based on the belief of both mean reversion and momentums patterns in housing prices. Moreover, we find support to the assertion that the effect of the belief in mean reversion dominates that in price momentums when the two are in conflict. Finally, our empirical evidence offers a refinement to the empirical literature on the price-volume correlation: in the market for new housing units. When prices are above (below) their long-term mean and recently experienced a negative (positive) trend, then the correlation between the price yield and the percent change in transaction volume is positive. When prices are above (below) their long-term mean and recently experienced a positive (negative) trend, then the examined price-volume correlation is negative.

It is important to note that our framework is potentially appropriate for explaining the price-volume correlation in any market that conforms to the two essential conditions: first, that one of the parties involved in the transaction (either the demand side or the supply side) experiences a greater flexibility with respect to the timing of the transaction, and, furthermore, that a non-negligible subgroup of that party expects a mean reversion price pattern. Based on our evidence, these conditions are apparently maintained in the new construction segment of the housing market.

Additionally, an important implication that emerges from the results is that, given consumers' perception of mean reversion and momentums in housing prices, developers can better assess future demand depending on past and ongoing prices. For example if

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Re-estimation of (8c) under the restriction of (11b*) allows a direct *t*-test of ψ_2 and the derivation of the confidence interval. We can further use this concept to derive the confidence interval for the estimated β under categories (3) and (4) [For more on this method see, for example, Ramanathan, (2002)].

recent prices are above the long-term mean price, consumers are likely to decrease the demand for new construction units in the foreseeable future, which may serve as an important input for decision-making regarding current land development.

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Appendix

Simulation:

Step 1: Following Equation (2), for a given x_0, generate $N\times(T+1)$ matrix of ask prices $x_{n,t}$, $n=1,2,\ldots,N$, and $t=0,1,\ldots,T$, where N and T denote the number of paths and number of periods, respectively.

Step 2: Compute $c_{n,T-1} = x_{n,T}e^{-r}$

Step 3: Regress $c_{n,T-1} = b_0 + b_1 x_{n,T-1} + b_2 x_{n,T-1}{}^2 + u_{n,T-1}$ applying an ordinary Least-Squares procedure. Then, compute $z_{n,T-1} = b_0 + b_1 x_{m,T-1} + b_2 x_{m,T-1}{}^2$.

Step 4: Note that if $x_{n,T-1} \le z_{n,T-1}$, then the buyer should exercise the option to purchase at time T-1 along path n. If, however, $x_{n,T-1} > z_{n,T-1}$, then the buyer is better off with the option alive. Denote the transaction price at time t along path n by $p_{n,t}$. Then, if $x_{n,T-1} \le z_{n,T-1}$, set $p_{n,T}=0$ (zero denotes no transaction) and $p_{n,T-1}=x_{n,T-1}$. Otherwise (that is, if $x_{n,T-1} > z_{n,T-1}$), then set $p_{n,T}=x_{n,T}$ and $p_{n,T-1}=0$.

Step 5: Compute $c_{n,T-2} = Min(p_{n,T} \times e^{-2r}, p_{n,T-1} \times e^{-r})$.

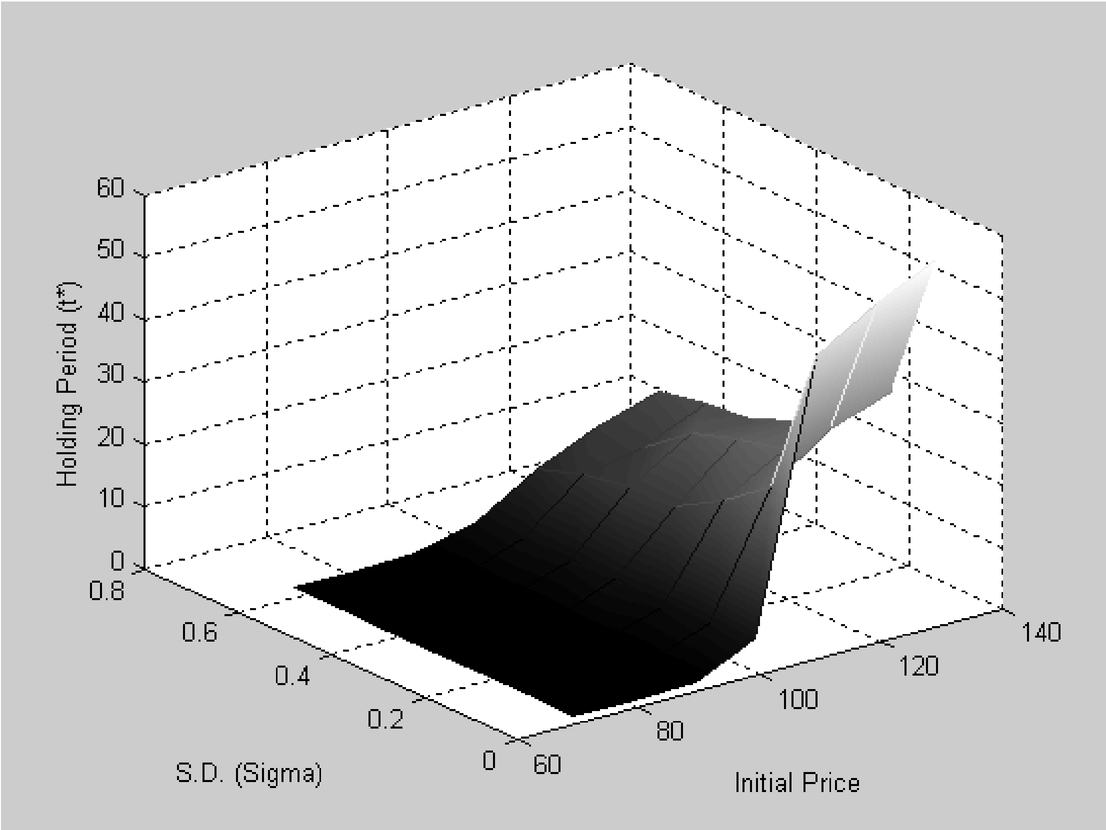
Step 6: Regress $c_{n,T-2} = b_0 + b_1 x_{n,T-2} + b_2 x_{n,T-2}{}^2 + u_{n,T-2}$ applying an ordinary Least-Squares procedure. Then, compute $z_{n,T-2} = b_0 + b_1 x_{n,T-2} + b_2 x_{n,T-2}{}^2$.

Step 7: If $x_{n,T-2} \le z_{n,T-2}$, set $p_{n,T}=p_{n,T-1}=0$ (zero denotes no transaction) and $p_{n,T-2}=x_{n,T-2}$; and if $x_{n,T-2} > z_{n,T-2}$, then set $p_{n,T-2}=0$ and maintain the results previously obtained for $p_{n,T-1}$ and $p_{n,T}$.

Step 8: Recursively repeat steps 6-8 for all n and $t=1,\ldots,T$-3. That is, compute $c_{n,t} = Min[p_{n,T}e^{-r(T-t)},\ldots,p_{n,t+1}e^{-r}]$. Regress $c_{n,t} = b_0 + b_1 x_{n,t} + b_2 x_{n,t}{}^2 + u_{n,t}$ applying an ordinary Least-Squares procedure. Then, compute $z_{n,t} = b_0 + b_1 x_{n,t} + b_2 x_{n,t}{}^2$. Finally, If $x_{n,t} \le z_{n,t}$, set $p_{n,T}=\ldots=p_{n,t+1}=0$ and $p_{n,t}=x_{n,t}$ and if $x_{n,t} > z_{n,t}$, then set $p_{n,t}=0$ and maintain the results previously obtained for $p_{n,t+1},\ldots, p_{n,T}$.

Step 9: Along each path n denote the period t at which $p_{n,t}>0$ by t^*_n. Then, compute the optimal stopping time, t^*, by averaging t^*_n across all paths. That is, $t^* = \frac{1}{N}\sum_n t^*_n$.

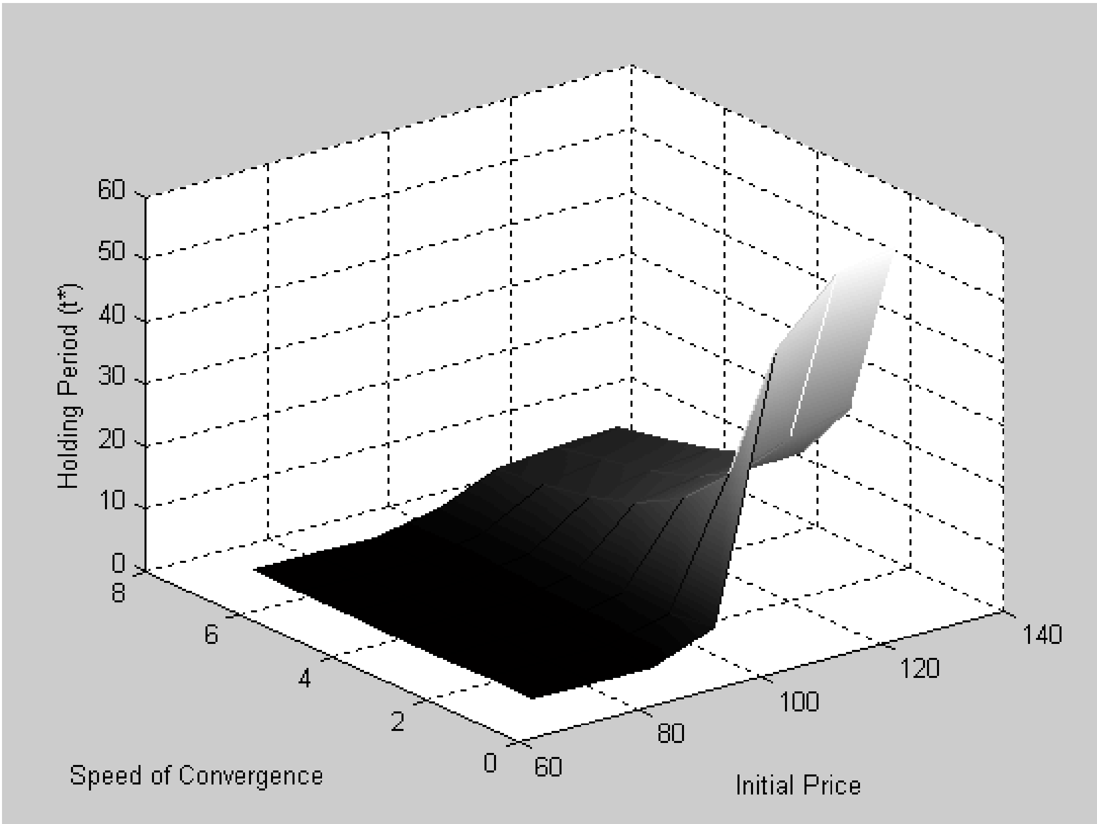
Figure 1: The optimal stopping time as a function of the price level and the price standard deviation



		sigma						
		0.01	**0.11**	**0.21**	**0.31**	**0.41**	**0.51**	**0.61**
	70	1	1	1	1	1	1	1
	80	1	1	1	1	1	1	1
price	**90**	1	1	1	1	1	1	1.14
	100	5.442	4.54	3.82	4.894	4.106	4.444	3.738
	110	48.18	23.938	18.072	13.812	13.686	11.988	9.536
	120	54.03	30.42	23.726	21.836	19.412	13.918	13.546
	130	58.374	33.672	27.736	22.262	19.144	18.252	16.566

Numerical values of other parameters: $r = 0.05, \gamma = 1, \bar{x} = 100$.

Figure 2: The optimal stopping time as a function of the price and the speed of convergence to the mean price



		gamma						
		1	**2**	**3**	**4**	**5**	**6**	**7**
	70	1	1	1	1	1	1	1
	80	1	1	1	1	1	1	1
price	**90**	1	1	1	1	1	1	1
	100	4.648	3.418	3.054	2.896	2.684	2.464	2.562
	110	46.314	23.076	15.672	11.558	9.1	7.632	6.63
	120	55.998	26.174	17.456	12.996	10.646	9.05	7.688
	130	57.574	28.602	18.048	14.144	11.556	9.542	8.058

Numerical values of other parameters: $r = 0.05, \sigma = 0.01, \bar{x} = 100$.

Tables 1a and 1b: Estimation of the weight $\hat{\lambda}$

Table 1a ($\rho = 0$)

Parameters / Lags	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6
$\hat{\lambda}$	0.90	0.90	0.88	0.85	0.85
$H_0 : \lambda = 0$	(26.58)*	(15.90)*	(27.41)*	(15.90)*	(14.47)*
$H_0 : \lambda = 1$	(–2.90)*	(–1.77)**	(–3.67)*	(–2.70)*	(–2.63)*
$\hat{\rho}$	0.76	0.93	0.81	0.85	0.81
$DW \approx 2(1-\hat{\rho})$	0.48	0.15	0.38	0.30	0.39
Min *ESS*	828.34	1287.58	1703.10	2157.17	2750.41
Likelihood	–270.98	–293.53	–306.77	–317.36	–328.06
Observations	112	111	110	109	108

Table 1b ($\rho \neq 0$)

Parameters / Lags	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6
$\hat{\lambda}$	–	0.90	0.88	0.85	0.85
$H_0 : \lambda = 0$	–	(17.95)*	(12.39)*	(19.93)*	(86.31)*
$H_0 : \lambda = 1$	–	(–2.0)*	(–1.66)**	(–3.39)*	(–15.71)*
$\hat{\rho}$	–	-1.80×10^{5}	-1.40×10^{-6}	1.48×10^{-5}	-2.86×10^{-5}
$DW \approx 2(1-\hat{\rho})$	–	2.00	2.00	2.00	2.00
Min *ESS*	–	1287.58	1703.10	2157.17	2750.41
Likelihood	–	–293.53	–306.77	–317.36	–328.06
Observations	112	111	110	109	108

Notes: The table presents the estimated weight ($\hat{\lambda}$) given to current as well as historical information for lags *k*=2,…,6 and the estimated serial correlation ($\hat{\rho}$). Each lag represents the nominal return on the housing price index over k months. To obtain these estimates we apply the Full Information Maximum Likelihood (*FIML*) procedure to the full sample. We also report the calculated *t*-statistics for testing the hypotheses λ=0 and λ=1. Other measures that appear in the table are the Durbin Watson Statistic (DW), Error Sum of Square (*ESS*), Maximum Likelihood value (Likelihood), and number of observations (Observations). In Table 1a (1b) we show the outcomes of the procedure when serial correlation is ignored (considered). For one case (lag 2) convergence has not been achieved. Numbers in parentheses are *t*-values. Significant values at 5% (10%) are marked with one (two) asterisk(s).

Table 2: Estimation of the correlation between volume (number of transactions) and recent price return vis-à-vis the long term mean price

Coefficients	Coefficient of:	k=2	k=3	k=4	k=5	k=6
$\hat{\beta}_0$	–	–0.34	–0.35	–0.52	–0.70	–1.65
		(–1.00)	(–1.48)	(–2.13)*	(–2.79)*	(–4.17)*
$\hat{\beta}_1$	*BM*	2.79	2.30	1.93	1.70	4.07
		(4.05)*	(9.76)*	(3.55)*	(2.20)*	(22.67)*
$\hat{\beta}_2$	*NEG*	1.19	2.18	1.17	0.88	2.00
		(1.33)	(23.79)*	(1.68)**	(1.01)	(6.41)*
$\hat{\beta}_3$	$BM \times NEG$	–4.57	–5.41	–4.00	–3.22	–4.46
		(–4.83)*	(–23.86)*	(–4.76)*	(–3.80)*	(–17.34)*
$\hat{\lambda}$	–	0.41	0.20	0.16	0.26	0.89
		(5.62)*	(10.19)*	(11.75)*	(8.14)*	(178.29)*
Category 1: $\hat{\beta}_0$	*BM*=0,*NEG*=0	–0.34 [–1.01,0.33]	–0.35 [–0.82,0.12]	–0.52 [–1.00,–0.04]	–0.70 [–1.20,–0.20]	–1.65 [–2.44,–0.86]
Category 2: $(\hat{\beta}_0 + \hat{\beta}_2)$	*BM*=0,*NEG*=1	0.85 [0.42,1.27]	1.83 [0.85,2.82]	0.65 [0.44,0.86]	0.18 [0.06,0.31]	0.35 [0.05,0.64]
Category 3: $(\hat{\beta}_0 + \hat{\beta}_1)$	*BM*=1,*NEG*=0	2.45 [2.05,2.84]	1.95 [1.59,2.31]	1.40 [1.33,1.52]	1.00 [0.68,1.32]	2.42 [1.65,3.21]
Category 4: $(\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3)$	*BM*=1,*NEG*=1	–0.92 [–1.61,–0.24]	–1.28 [–1.79,–0.78]	–1.42 [–1.72,–1.11]	–1.33 [–1.34,–1.32]	–0.04 [–0.80,0.74]
$\hat{\beta}_0\hat{\lambda}$	*BM*=0,*NEG*=0	–0.14	–0.07	–0.08	–0.18	–1.47
$(\hat{\beta}_0 + \hat{\beta}_2)\hat{\lambda}$	*BM*=0,*NEG*=1	0.35	0.37	0.10	0.05	0.31
$(\hat{\beta}_0 + \hat{\beta}_1)\hat{\lambda}$	*BM*=1,*NEG*=0	1.01	0.39	0.22	0.26	2.15
$(\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3)\hat{\lambda}$	*BM*=1,*NEG*=1	–0.38	–0.26	–0.22	–0.35	–0.03
$\hat{\rho}$		-1.3×10^{-4}	-3.6×10^{-10}	-2.1×10^{-6}	1.83×10^{-5}	1.37×10^{-4}
$DW \approx 2(1-\hat{\rho})$		2.00	2.00	2.00	2.00	2.00
ESS		759.80	1137.10	1502.78	1985.32	2567.17
Likelihood		–266.14	–286.90	–299.89	–312.83	–324.34
Observations		112.00	111.00	110.00	109.00	108.00

Notes: The table presents the estimation results of selected parameters and their interpretation for lags k=2,…,6.. To obtain these estimates we incorporate two dummies and their interaction term: the dummy variable *BM* receives 1 if the current housing price index is below the mean predicted housing price index and 0 otherwise. The dummy variable *NEG* receives 1 if the computed recent price-index return is negative and 0 otherwise. The coefficient $\hat{\beta}$, the marginal correlation between transaction volume and the current price yield, is defined as $\hat{\beta}_0 + \hat{\beta}_1 BM + \hat{\beta}_2 \times NEG + \hat{\beta}_3 BM \times NEG$. We report its calculated four different values. The coefficient $\hat{\lambda}$ is the weight given to current as well as historical information. Numbers in parentheses are *t*-values. Significant values at 5% (10%) are marked with one (two) asterisk(s).

We also report the two-tailed 5% confidence intervals for all categories, where the respective critical value is 1.985.