# Game Theoretic Analysis of the Feedback Loop Caused by Widely Available Computer Estimation on Market Values

**Viorel Silaghi, Zobaida Alssadi, Ben Mathew, Majed Alotaibi, Ali Alqarni, Marius Silaghi**
Florida Institute of Technology

**Abstract**

Public availability of computer generated predictions can change the markets and its impact is here investigated with a game theoretic approach. Real estate inflation is not a new phenomenon but its consistent and almost monotonous persistence over unusually many years, coinciding with new prominence of public estimation information from successful Mass Real Estate Estimators (MREE) already caused various independent research organizations to investigate potential links. What we model is a repetitive theoretical game between the MREEs and the home owners, where each player has secret information and expertise. In contrast to competing results, for our model and simulations a restriction of MREE-style price estimation availability to opt-in properties may help partially reduce an inflationary pressure.

## Motivation and Approach

Mass Real Estate Estimators (MREE) have attained a prominent position in the estimation of prices for houses (Lambert 2022), such that in sellers' markets offers to purchase houses at a price lower than MREE's estimation were for a long time seen as non-starters (Glynn 2020). Recent empirical studies of impacts of MREEs in (Troncoso et al. 2023; Zhang, Goh, and Sun 2023; Barnwell and Fournel 2022) show that sellers tend to earn less by listing under the MREE value, even if they may close faster. It is also shown that listings tend to deviate with amounts that are mainly above the MREE estimation. The catch is that proprietary predictions like those from a MREE are influenced by the selling price of neighboring homes (Fu, Jin, and Liu 2022).

Realtors suggest the MREE's estimation errors to 20% of classic appraisal approaches (Harney 2017). We model a phenomenon where, any errors in a widely available MREE's price estimations coupled with the algorithm that feeds them back into selling prices leads to a ratchet effect.

**Competing models** A study and simulation of MREEs impact on markets in (Fu, Jin, and Liu 2022) assume different errors in estimation produce disturbances in opposite directions, that would eventually cancel out, and do not address the game theoretic phenomena we raise, where errors in both directions build on each other towards a unidirectional disturbance. The correlation with experimental data that they note could potentially also be due to the fact that the main studied disturbance for the situation data analysed is related to external events, outside the human-algorithm loop, in the impacts of the COVID emergency handling.

**New observation at the foundation of our model.** The value of a house is a composition of its location value with the value of the construction features. When the estimation from MREE for a house is *underestimating* the house by $\Delta$ to price $x$, the owner or competing bidding buyers will know and transaction the house at the right price $x + \Delta$. At that point the MREE will wrongly conclude that there was an inflation of the location by $\Delta$ and will raise neighboring houses estimates with an impact of the $\Delta$ propagation.

Alternatively, when the estimation from MREE for a given house is *overestimating* a house by $\Delta$ to a price $x$, the buyers will be emboldened to trust the MREE reputation and the seller happily adopts the MREE price. This is leading to an immediate actual local inflation by $\Delta$ that propagates in the neighborhood since better houses around will have arguments to be assessed higher.

As such, both overestimating and underestimating errors generate inflation proportional with absolute error.

**Definition 1 (REPP)** *A Real Estate Prediction Problem (REPP) of a MREE is defined by a tuple $\langle G, T, P, \Lambda \rangle$ where G is a graph $G(N, E)$ consisting of a set of nodes N representing houses and arcs E representing distances between the houses. An edge $e \in E$ corresponds to a distance between the nodes.*

*Each node $n \in N$ is a tuple $\langle v, u, \lambda^{n,0}, \rho^{n,0} \rangle$ where $v$ is the value of the house from the perspective of its construction features as estimated by MREE and $u$ is the objective actual construction features value estimated by owners assumed to be experts, while $\lambda^{n,0}$ is the value of the location at the initial time $t_0$, and $\rho^{n,0}$ is a market value adjustment of the construction features at the initial time.*

*$T$ is a vector of transactions, each $k^{th}$ transaction $\theta \in T$ being a tuple $\langle t_\theta, c_\theta, i_\theta \rangle$ where $t_\theta$ is the day of the transaction contract, $c_\theta$ is the day of transaction contract closing,*

*and $i_\theta$ is the transacted node. The vector $T$ is ordered by closing time.*

*For each node $n$, $\lambda^{n,k}$ and $\rho^{n,k}$ are variables specifying the location and the construction market value estimations after the $k^{th}$ transaction closing, respectively. For a given $k$, the set of variables $\lambda^{n,k}$ is denoted $\lambda^k$ and the set of variables $\rho^{n,k}$ is denoted $\rho^k$.*

*The price $p_\theta$ of each transaction $\theta$ is given by a function $P(G, \theta, \lambda^{c(\theta^k)}, \rho^{c(\theta^k)})$ where the $c(\theta^k)^{th}$ transaction is the last one closing before the contract date $t_{\theta^k}$ of $\theta^k$.*

*Each closing of $k^{th}$ transaction $\theta^k$ with price $p_{\theta^k}$ has an impact on the estimations of the location value of each node $n$, $\lambda^{n,k}$, given by a function $\Lambda(n, G, \theta^k, p_{\theta^k}, \lambda^{k-1})$, which cannot access the components $u$ of nodes in $G$. Also, after $\theta^k$ the construction feature values $\rho^{n,k}$ are given by a function $\Pi(n, G, \theta^k, p_{\theta^k}, \lambda^{k-1}, \rho^{k-1})$.*

*The problem is recomputing estimates after transactions.*

**Studied REPP functions** In simulations we take:

- $P$ defined as:
$p_{\theta^k} = P(G, \theta^k, \lambda^{c(\theta^k)}, \rho^{c(\theta^k)}) = \lambda^{i_{\theta^k}, c(\theta^k)} + \max(v_{i_{\theta^k}}, u_{i_{\theta^k}} + \rho^{i_{\theta^k}, c(\theta^k)})$.
- $\Lambda$ defined as:

$$\lambda^{n,k} = \Lambda(n, G, \theta^k, p_{\theta^k}, \lambda^{k-1}) = \quad (1)$$

$$= \lambda^{n,k-1} + \left(\frac{p_{\theta^k} - b * v_{i_{\theta^k}}}{1 + a * v_{i_{\theta^k}}} - \lambda^{i_{\theta^k}, k-1}\right) * ReLU\left(\frac{R - d(n, i_{\theta^k})}{R}\right) \quad (2)$$

  with b=1 and a=0, while R is a maximum influence distance and $d(n,m)$ is the Euclidean distance between nodes $n$ and $m$. In experiments with grid maps, $\frac{R-d(n,i_{\theta^k})}{R}$ is replaced with $\frac{R_x-d_x(n,i_{\theta^k})}{R_x}\frac{R_y-d_y(n,i_{\theta^k})}{R_y}$ where $R_x$ and $R_y$ are maximum influence distances on $x$ and $y$ coordinates, respectively, and $d_x()$ and $d_y()$ are Euclidean distance functions along projections on the $x$ and $y$ coordinates. $ReLU(x)$ is defined as $max(0, x)$.
- Function $\Pi$: $\rho^{n,k} = \Pi(n, G, \theta^k, p_{\theta^k}, \lambda^{k-1}, \rho^{k-1}) =$
$$= \rho^{n,k-1} + ReLU\left(\frac{p_{\theta^k} - MREE_{\theta^k}}{a * \lambda^{i_{\theta^k}, k-1} + b} - u_{i_{\theta^k}}\right) * ReLU\left(\frac{R - d(n, i_{\theta^k})}{R}\right).$$
  Where $MREE_{\theta^k} = \lambda^{i_{\theta^k}, k-1} + v_{i_{\theta^k}, k-1}$ is the MREE public estimation in the moment of the closing.

## Simulations Discussion

Details of the simulation parameters are given in the extended version (VS 2022). Figure 1 shows a linear relation with a slope that is proportional with both the absolute error range and the neighborhood size, as expected from the theoretic model. The largest gain in inflation occurs when the estimation neighborhood size increases from 5 to 10 houses distance. Figure 2 shows impact of construction value on inflation. In Figure 3 it can be observed that when everyone opts-in the MREE (the blue line) the inflation is maximized.

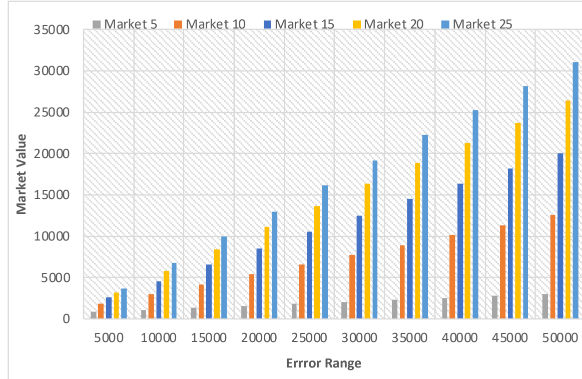


Figure 1: Market inflation as function of absolute error range, various neighborhood sizes: 5 houses to 25 houses

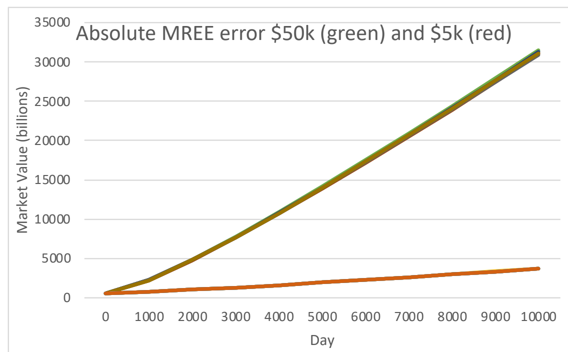


Figure 2: The inflation is shown to be driven faster in the presence of expensive houses (neighborhood size of 25).

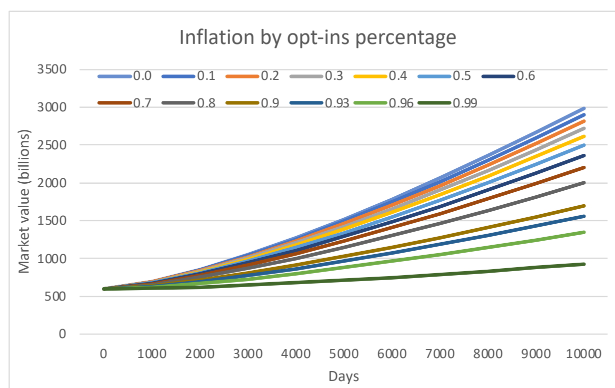


Figure 3: Each curve is associated with a percentage of people who did not opt in.

Experiments do not factor in other external constraints, like the lack of money in the system, overbuilding, and population decrease. Given phenomena revealed by experiments for our model, equilibrium in their presence can occur at values that are different from the ones in the absence of the MREE AI-human feedback loop.

## References


[Barnwell and Fournel 2022] Barnwell, J.-L., and Fournel, J.-F. 2022. Seller's (mis) fortune in the housing market: Directed search in online real estate platforms.

[Fu, Jin, and Liu 2022] Fu, R.; Jin, G. Z.; and Liu, M. 2022. Human-algorithm interactions: Evidence from zillow. com. Technical report, National Bureau of Economic Research.

[Glynn 2020] Glynn, C. 2020. Intense competition pushes share of homes selling above list to record high. https://www.zillow.com/research/home-sales-above-list-price-2020-28328/.

[Harney 2017] Harney, K. R. 2017. Zillow faces lawsuit over 'zestimate' tool that calculates a house's worth. https://www.washingtonpost.com/realestate/zillow-faces-lawsuit-over\protect\discretionary{\char\hyphenchar\font}{}{}zestimate-tool-that-calculates-a-houses-worth/2017/05/09/b22d0318-3410-11e7-b4ee-434b6d506b37_story.html.

[Lambert 2022] Lambert, L. 2022. The housing market isn't normalizing–zillow predicts the wildest home price swing still awaits. https://fortune.com/2022/03/20/zillow-predicts-wildest-home-price-swing-still-awaits/.

[Troncoso et al. 2023] Troncoso, I.; Fu, R.; Malik, N.; and Proserpio, D. 2023. Algorithm failures and consumers' response: Evidence from zillow. *Available at SSRN 4520172*.

[VS 2022] 2022. Public AI on house price estimations through zillow may influence a monotonic house price increase and inflation forever according to simulations. https://www.overleaf.com/read/yttcffkrhvjf#7120e1. Uploaded in overleaf on February 15, 2022.

[Zhang, Goh, and Sun 2023] Zhang, X.; Goh, K. Y.; and Sun, C. 2023. The effect of platform-developed ai price recommendations adoption on e-commerce platform sales distribution.