

# Housing Price Transmission Mechanism for Monetary Policy: An Application of Deep Learning for Macroeconomic Modelling

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## Abstract

Placeholder

## 1 Introduction

There is a growing literature including the work of Duarte (2018), Azinovic et al. (2019), and Maliar et al. (2021) that considers how neural networks can be used to approximate the solution to macroeconomic models. These papers suggest that this methodology can be used to solve highly complex economic models which might have previously been considered computationally intractable. In particular, Han, Yang, et al. (2021) suggest that the neural network methodology is particularly useful in contexts which are both *high-dimensional* and *non-linear*. This is because while neural networks perform admirably in this type of environment (citation here), existing techniques used in economics fall short here. Projection can be used in high-dimensional settings, but by definition fails to handle non-linearities (citation here). Conversely, perturbation can handle non-linearities, but quickly becomes intractable as the dimension of the state space grows (citation here). This paper will consider one policy relevant application that possesses both of the aforementioned properties, such that the neural network methodology will be required in order to adequately estimate a solution.

The model consists of heterogeneous households who can invest in a return-bearing asset (housing), but only if they possess a requisite level of wealth to pay a fixed cost (down-payment). This asset has the benefit of being safe from inflation, but is associated with a cost that varies with the policy rate (mortgage payments). If agents are unable to afford the fixed cost they will have to store their wealth in (cash or risk-free bond). Since the agents face a cut-off, the model contains a distinct non-linearity, and to some extent as a result of this the model is not subject to Krusell-Smith aggregation (Krusell & Smith, 1998). Therefore, the heterogeneity between agents is non-trivial, and the solution lies

in a high-dimensional space, so in order to solve the model a neural network will be employed.

The main result of the model is a monetary transmission mechanism that acts on housing prices and inequality, which is particularly relevant to policy in the post-financial crisis era. The increase in inflationary pressure resulting from loose monetary policy statically increases inequality, but more importantly, it has the dynamic effect of causing fewer agents to be able to pay the fixed cost to own the housing asset. Since monetary policy has a direct impact on the behaviour of only the asset-bearing agents this results in a dampening of the effect of future monetary policy action.

## 2 Literature Review

## 3 Model

### 3.1 Households

The model contains a discrete mass (for sake of simulation) of  $n$  agents, who in each period may be either an asset-owning or renter agent. Since the same agent can switch between these states dynamically, we will consider a value function approach to specifying this model. Consider first the case of the renter agent. They can only store their wealth in cash that pays no interest, until they can amass enough wealth to surpass the asset fixed cost. In this case the agent is able to pay  $\phi p_t^a$  or more to buy one unit of the return bearing asset, while the rest is borrowed as debt that is amortized linearly over subsequent periods. In order to simplify notation let the wealth in each period  $t$  a renter agent indexed  $i$  be  $\omega_{it}^{NA} = w_t l_{it} + m_{it} - i_t d_{it}$  (even though  $l_{it}$  is a choice variable). Given these definitions, a renter agent's value function is:

$$\begin{aligned} \max_{c_{it}, l_{it}, a_{it+1}} V_{it}^{NA}(0, m_{it}, d_{it}) = & u_i(c_{it}, l_{it}) + \beta [ \\ & \mathbb{I}\{\omega_{it}^{NA} - p_t c_{it} \geq \phi p_t^a\} V_{it+1}^A(\frac{a_{it+1}}{p_t^a}, \omega_{it}^{NA} - p_t c_{it} - p_t^a a_{it+1}, (1 - i_t) d_{it}) + \\ & (1 - \mathbb{I}\{\omega_{it}^{NA} - p_t c_{it} \geq \phi p_t^a\}) V_{it+1}^{NA}(0, \omega_{it}^{NA} - p_t c_{it}, (1 - i_t) d_{it}) ] \end{aligned} \quad (1)$$

The once an agent owns a non-zero amount of the asset they will benefit each period from amortization and any inflation that occurs in asset prices. However, they will also have to pay interest on their previous asset purchases. For simplicity, assume this interest is equal to the policy rate (in some extension we can model the financial sector who may charge some variable markup here). If the agent's wealth falls sufficiently low, they may be forced to liquidate some of their assets. Assume that if the agent's net worth falls below  $\phi p_t^a$  they are forced to liquidate all of their assets and become a renter agent. The value function for the asset-holding agents is:

$$\begin{aligned}
& \max_{c_{it}, l_{it}, a_{it+1}} V_{it}^A(a_{it}, m_{it}) = u_i(c_{it}, l_{it}) + \beta[ \\
& \mathbb{I}\{(1 + r_t + \pi_t^a - i_t) p_t^a a_{it} + w_t l_{it} + m_{it} - p_t c_{it} \geq \phi p_t^a\} V_{it+1}^A(\frac{(1 + r_t + \pi_t^a - i_t) p_t^a a_{it} + w_t l_{it} + m_{it} - p_t c_{it}}{p_t^a}, 0) + \\
& (1 - (1 + r_t + \pi_t^a - i_t) p_t^a a_{it} + w_t l_{it} + m_{it} - p_t c_{it}) V_{it+1}^{NA}(0, (1 + r_t + \pi_t^a - i_t) p_t^a a_{it} + w_t l_{it} + m_{it} - p_t c_{it})] \\
& \quad (2)
\end{aligned}$$

Note that the asset-owning agent will, in

## 4 Method

## 5 Results

## 6 Conclusion

## References

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