Home Selling and Tax Reform*

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Abstract

The Tax Cuts and Jobs Act (TCJA) of 2017 reduced a homeowner's tax deduction benefits from deducting mortgage interest and property taxes. Since a seller can capitalize the tax deduction benefits related to housing into a housing price, the TCJA affects the seller's listing price decision and market outcomes. To investigate a seller's listing price choice and market outcomes in response to changes in various types of tax provisions related to housing, I develop a structural model in which the seller chooses the listing price to maximize his payoff, the sales price net of his waiting cost. Using the estimated model, I find that the TCJA causes the seller to choose a listing price that is approximately 7.38% lower, which leads to about a 7.30% reduction in the sales price and about one week reduction in the time on the market. The TCJA mostly impacts high income households and high property tax payers. In addition, based on the bills introduced in the 118th Congress, I evaluate the effect of increasing the state and local tax (SALT) cap after the TCJA is implemented in three different SALT limits. As the SALT cap increases, both the listing price and market outcomes are inclined to return to levels closer to those predicted results of the pre-TCJA tax regime. Moreover, those most affected by the TCJA, specifically high income households and high property tax payers, increase their listing prices the most, consequently leading to the most increases in their sales prices and time on the market compared to others. Finally, I quantify the impact of eliminating the mortgage interest deduction on the seller's listing price and market outcomes, assuming that the TCJA has expired. Based on the model projection, the seller's listing price decreases by approximately 16.43%, the sales price reduces by 16.34%, and time on the market increases by about two weeks on average when the mortgage interest deduction is eliminated.

Keywords: Housing, Home Selling, Listing Price, TCJA, SALT, Mortgage Interest

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1 Introduction

The federal government of the United States incentivizes home ownership through many provisions in the income tax code. Homeowners can get benefits by choosing an itemized deduction when they file their return. Among the itemized deduction items, the property tax deduction and mortgage interest deduction are major subsidies to homeowners. According to the Joint Committee on Taxation (2017), homeowners received more than $95 billion in benefits from deducting mortgage interest and property taxes on their tax returns.

A recent tax reform, known as the Tax Cuts and Jobs Act (TCJA) of 2017, made significant changes to the rules for individuals, especially homeowners. The TCJA modified the deduction rules for itemized deductions.[1] For the case of "Married couples filing jointly," the mortgage interest deduction limit was reduced to $750,000 of debt. The most influential change is about the state and local tax (SALT) deduction, which allows for deducting property taxes. After the TCJA became effective, the SALT deduction was subject to a total cap of $10,000. Also, the TCJA increased the standard deduction amount to $24,000.[2]

Changes in tax provisions related to housing affect the benefits of owning a house. These changes affect the seller's behavior while selling the house and thus lead to changes in the housing market outcome, such as sales price and time on the market, for the seller. This is because the benefit of deducting property tax and mortgage interest can be capitalized into a housing price (Poterba, 1984; Poterba, 1992; Hilber and Turner, 2014; Rappoport, 2017; Rappoport, 2019; Davis, 2019). Changes from the TCJA are expected to give more incentive to the household to choose the standard deduction rather than the itemized deduction. Also, when the homeowner chooses the itemized deduction, the allowance to deduct mortgage interest and property taxes permits the homeowner to reduce these expenses. After the TCJA, decreased deduction benefits from deducting mortgage interest and property taxes make housing less valuable. Because the seller capitalizes the change in tax deduction benefits related to housing into his housing market value, the TCJA affects his decision of the listing price and housing market outcomes when he sells the house.

[1]When individuals choose itemized deduction, they can deduct state and local tax, mortgage interest, and charitable giving they paid in a year.

[2]Also, the TCJA lowered the marginal income tax rates and changed the tax brackets.

Motivated by the recent tax reform, this paper investigates a seller's listing price choice in response to changes in various types of tax provisions related to housing. To answer this question, I build a structural model that focuses on a seller's behavior in terms of the listing price, sale price, and time on the market for the house. Due to the lack of the buyer's side information in housing transaction data, modeling for the seller's strategic choice of listing price and the buyer's side together posed a problem in empirical housing literature. To overcome this data limitation, I incorporate the hazard rate and survival function into the model of a seller's payoff maximization. The seller decides to sell his house as a given and chooses the listing price to maximize his payoff from the housing transaction, assuming that he knows a survival function for the time it takes to sell the house, conditional on his listing price. The survival function of the house changes depending on the seller's listing price choice and the predicted market value of the house which varies by the estimated tax deduction value for each house. To maximize his payoff, the seller needs to adjust the listing price as the tax deduction benefit related to housing changes. The sales price is determined by the seller's listing price and time on the market for the house. While the seller waits for the housing transaction, he incurs a waiting cost of not selling the house every week, which differs by demographic characteristics.

The main contribution of this paper is to develop a framework for capitalizing the tax deduction benefit into housing value and making it affect a seller's listing price choice. Also, through the model mechanism, the seller considers the sales price and time on the market for the house simultaneously through his listing price choice, which describes the features of the seller's behavior in the housing market. Most of the empirical literature on housing has focused either on the determinants of the sales price, on the relationship between the listing price and time on the market, or on the search behaviors of either the seller or buyer. Selling a home is an important problem for a household, but the seller's listing price choice and waiting cost with demographics are rarely studied. Also, tax-induced changes in the subsidy for housing through the mortgage interest and property tax deduction can have an important capitalization effect on housing prices. Most literature deals with the tax-induced changes in the subsidy for housing and housing prices, but there is less study about individual behavior within the microstructure of the housing market. In this paper, I incorporate the capitalization effect of tax benefits related to housing into the seller's home selling problem. I am able to compute the tax deduction benefit related to housing because the data I use provides the transaction information and demographics of the seller.[3] The model I develop can show how the individual seller responds to the changes in their home value from the tax deduction benefit related to housing when he lists his house. In this paper, I do not explicitly model the buyer's behavior and the bargaining process that leads to housing transaction. To account for these features, I specify a simplified model of the buyer's side in a non-structural method. I combine survival analysis with a seller's payoff maximization problem. The model framework can also be extended to incorporate the capitalization effect of other housing-related benefits, such as the neighborhood effect, on housing value in order to research the seller's listing price choice and market outcomes.

I estimate the model using Maximum Simulated Likelihood estimation. The estimation results suggest that, when either the listing price is high, or the predicted market value of the house is low, the probability of sales of the house in week t decreases conditional on the house not having sold prior to week t. In the sample, the seller has about a \$6,860 waiting cost per week on average, and it does not significantly differ across demographic information. In addition, I find that the standard deviation of the county-specific random effect is quite large, implying that the heterogeneity across counties is an important source of the heterogeneity. I demonstrate that the data fit reasonably well with the estimated model by comparing the prediction of the model and actual data through local linear kernel regression.

Through the estimated structural model, I perform counterfactual analyses of several tax reform scenarios that lead to changes in tax provisions related to housing. I quantify the impact of the TCJA and different capping criteria on the SALT cap under the TCJA based on the bill introduced in the 118th Congress to the seller's listing price choice and relevant market outcomes. To my knowledge, this paper is the first to study the impact of adjusting the SALT cap under the tax regime of the TCJA on market outcomes.[4] Also, I evaluate the effect of eliminating the mortgage interest deduction through model simulation.

I find that, after the passage of the TCJA, the seller chooses a listing price about 7.38% lower to sell his house, resulting in an approximately 7.30% decrease in the sales price and about one week

[3]Most housing data come from the Multiple Listing Service, and it has housing transaction information and housing attributes. It does not have any demographic information of the seller. I use survey data from the National Association of Realtors. The details of the data I use are discussed in Section 2.

[4]Relevant literature studied the impact of the TCJA itself. Recently, Bishop *et al.* (2023) analyzed the impact of SALT cap elimination on the user cost rate of homeownership.

reduction in time on the market for the house. The impact of the TCJA on the listing price and market outcomes varies depending on the household's income level and property tax amounts. The TCJA has the most significant impact on high income households and those who pay high amounts in property taxes.

When making adjustments to the SALT cap based on the SALT Marriage Penalty Elimination Act, SALT Relief Act, and Tax Relief for Middle Class Families Act, I raise the SALT deduction limit in three different scenarios: $20,000 for joint returns only; $50,000 for single returns and $100,000 for joint returns; $100,000 for single returns and $200,000 for joint returns. After the implementation of the TCJA, as the SALT cap increases, both the listing price and market outcomes tend to return to levels closer to those predicted before the TCJA. However, they do not return fully to the exact levels of the pre-TCJA tax regime because the standard deduction is still doubled compared to before the TCJA in these simulations. In addition, as the SALT cap increases, the high income households and households paying high amounts in property taxes, who are most impacted by the TCJA, raise their listing prices the most compared to others when selling their houses. Consequently, this leads to an increase in both the sales price and the time on the market for their house.

Lastly, I remove the mortgage interest deduction under the assumption that the TCJA has expired. This leads to a decrease in the listing price and sales price by about 16% each and a reduction in time on the market by about two weeks. The impact of removing the mortgage interest deduction is greater than that of the TCJA. Furthermore, the effect of eliminating the mortgage interest deduction on the listing price and market outcomes does not differ across income levels.

This paper is related to the large body of empirical literature on the relationship between listing price and housing market outcomes, including Miller and Sklarz (1987), Yavas and Yang (1995), Knight (2002), Anglin *et al.* (2003), Merlo and Ortalo-Magne (2004), and Haurin *et al.* (2010). Many works found a positive relationship between listing price and time on the market. Most previous papers in this field have paid attention to the relationship itself rather than focusing on how the seller's listing price choice is determined and how market outcomes are affected by exogenous changes. Carrillo (2012) estimated an equilibrium search model of the buyer and seller and showed that both listing and sales prices decrease when more listing information is available or when the commission rate is reduced. Due to the lack of adequate data for empirical research on housing transactions, such as the buyer side information related to each house, it has been limited to research on the strategic choices of both the seller and buyer. However, using a novel data set that includes listing price changes and offers made on each house, Merlo *et al.* (2015) studied the seller's listing price choice, whether or not the seller accepts offers, and the decision to withdraw the house from the market. Instead of explicitly modeling the buyer's behavior and the bargaining game, they calibrated the buyer's bid function to solve the seller's strategic choice.

This paper is also related to studies about the effect of the TCJA on the housing market. Martin (2018), Rappoport (2019), and Sommer and Sullivan (2021) found that the house price is reduced by the TCJA. In contrast to Martin (2018) and Rappoport (2019), Sommer and Sullivan (2021) showed the decline in the house price is marginal. The different results may be because Sommer and Sullivan (2021) omit the sources of heterogeneity for the sake of model tractability. For example, they did not take into account the differential impacts of the SALT deduction limit across property tax rates and housing prices. Li and Yu (2022) showed that the growth rate of home value declines, but the effect differs by geographical location depending on property taxes. Through micro-level analysis, Ambrose *et al.* (2022) found that the TCJA reduces tax subsidies. Hembre and Dantas (2022) showed that the TCJA reduces the homeownership subsidies, which leads to a decline in homeownership rate and home value. Coen-Pirani and Sieg (2019) found that the TCJA provides an incentive for older, high-productivity households to relocate to less expensive, lower-tax cities. Bishop *et al.* (2023) developed a way of calculating the cost of homeownership and analyzed the effect of the TCJA on homeownership cost.

The rest of the paper proceeds as follows. Section 2 presents the data description. Section 3 introduces the seller's payoff maximization model. Section 4 explains the estimation procedure, and Section 5 shows the estimation results. I present the counterfactual analyses in Section 6 and conclude in Section 7.

2 Data Description

I mainly use the survey data from the National Association of Realtors (NAR) for the main estimation procedure. I explain the details of the NAR survey in Section 2.1. Then, I introduce supplemental data for the estimation procedure in Section 2.2.

2.1 NAR Surveys

The choice of data is motivated by two features of the NAR surveys: (i) housing transaction information and housing attributes and (ii) demographic information of the sellers. Because I model the seller's listing price choice, the data should include the listing prices, housing market outcomes, and relevant housing attributes. Also, in order to compute the tax deduction benefits related to housing, demographic information of each homeowner is required. It helps me to approximate the homeowner's tax schedule and also can be used to evaluate the seller's waiting cost in the model.[5]

The main data source is separate surveys of individual home sellers conducted by the Research Division of the NAR. Because this survey is annual and nationwide, the sample in the survey includes housing transactions from 2011 to 2018. For each house in the sample, I know the transaction information (sold year and month, final selling price, original listing price, time on the market for the house), housing attributes (type of home, year built, square footage, number of bedrooms and bathrooms), and the seller's demographics.

Table 1 reports descriptive statistics of the housing transaction in the sample. The sample includes 7,474 housing transactions. The seller spent on average 12.8 weeks on the market with a standard deviation of 17.9. Figure 1 presents the distribution of time on the market across all houses included in the sample. Table 1 and Figure 1 show that most houses are sold in a short time. In the sample, 50% of houses are sold within five weeks after being listed. However, 25% of houses took more than 15 weeks to be sold, and about 5% of houses took a significantly longer time, such as more than a year, to be transacted.

Previous literature also provides information on sellers' time on the market in different countries. According to Merlo and Ortalo-Magne (2004), sellers spent 11 weeks on average from 1995 to 1998 in England's housing market. Also, Fan *et al.* (2023) showed that home sellers in Beijing spent about 5.4 weeks on the market on average. The time on the market seems associated with the types of houses in the housing market. As the share of detached houses increases in the housing market, sellers tend to spend less time on the market.[6]

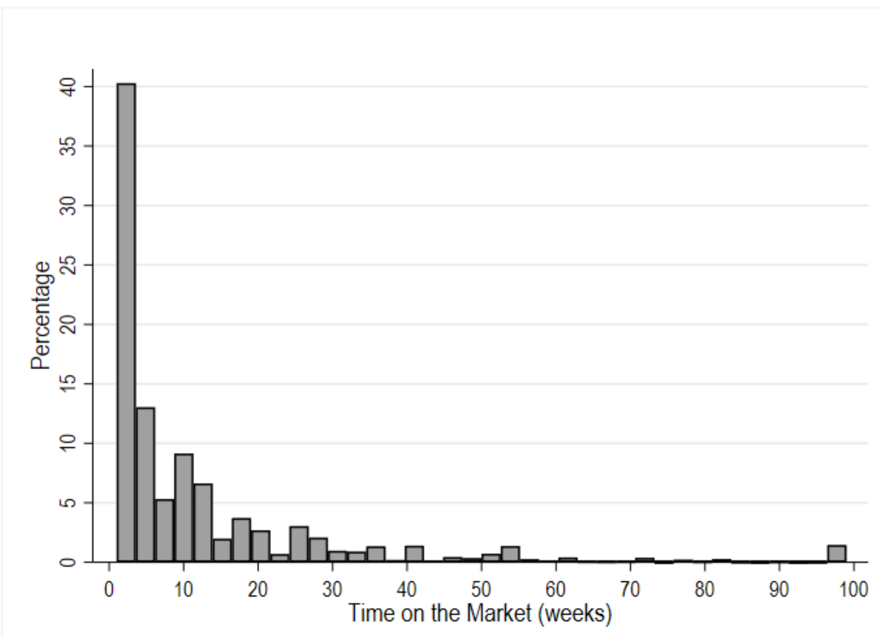
[5]The details about approximating the expected homeowner's tax schedule are discussed in Section 3.1.3.
[6]I describe the types of houses in the data in Table 3. I explain more details later.

Table 1: Descriptive Statistics of Housing Transaction in the Sample

Variable	Mean	Sd	Min	P25	P50	P75	Max
Sales price ($ thousands)	283.8	157.2	65.0	169.9	241.5	350.0	999.0 [7]
Original listing price ($ thousands)	294.5	162.3	100.0	175.0	250.0	360.0	1,100.0
Time on the market (weeks)	12.8	17.9	1.0	2.0	5.0	15.0	99.0

Furthermore, in Figure 1, I observe a spike near a point where the time on the market is 100. Since the NAR survey allowed respondents to respond to their time on the market up to 99, researchers cannot know whether the seller spent precisely 99 weeks or more than 99 weeks to sell the house. Therefore, I use right censoring in the model for the observations whose time on the market is reported as 99.

Figure 1: Distribution of Time on the Market



The listing price ranges from $100,000 to $1,100,000. I drop the observation whose listing price is lower than or equal to $100,000.[8] The average listing price is $294,500, and the average sales price is $283,800. Among the houses in the sample, the sales prices were higher than, equal to, or

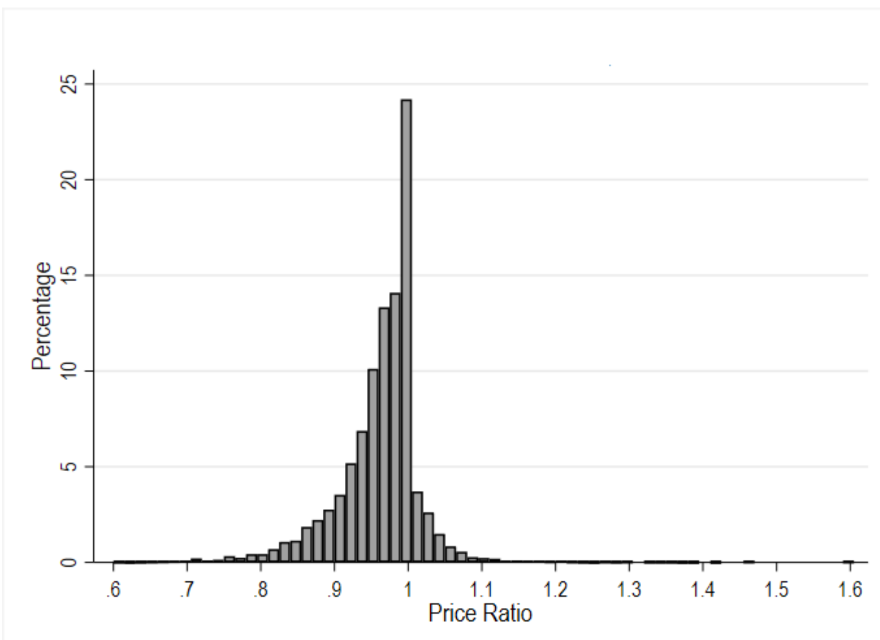
[7] It mean the sales price is $999,000

[8] I use a logarithmic price scale and dollar unit in $100,000 in the estimation procedure. For example, when the listing price is less than $100,000, the log value of the listing price is negative.

lower than the listing prices.

I present the distribution of the ratio of the sales price to the listing price in Figure 2. If the ratio of sales price to listing price is greater than 1, it means that the house was sold at a price higher than the listing price. If the ratio of sales price to listing price is lower than 1, it means that the house was sold at a price lower than the listing price. In Figure 2, most houses are sold below the listing price in the sample. In detail, I observe that approximately 70% of the houses were sold below their listing prices, 18% were sold exactly at their listing prices, and the remaining 12% were sold above their listing prices. According to Han and Strange (2014), the share of housing transactions that the sales price is higher than the listing price has increased since 1993, and the share was about 10% in 2010.[9] This trend implies that housing transactions should be modeled to incorporate this feature.

Figure 2: Ratio of Sales Price to Listing Price



[9]Also, the share of housing transactions that the sales price is higher than the listing price was 3.49% in the Beijing housing market (Fan *et al.*, 2023).

Table 2: Number of Reductions in Listing Price in the Sample

Number of Reduction in Listing Price	Percentage
0	53.58
1	22.33
2	12.00
3	6.49
4	2.72
5 or more	2.88

Another feature is that the listing prices are highly sticky in the housing market. In Table 2, approximately 54% of the sellers did not change their listing price before the transaction happened, 22% of the sellers changed their listing price only once, and 12% of the sellers changed twice in the sample. This feature is common across other housing data.[10]

In Table 3, I present descriptive statistics of houses in the sample. The share of detached single-family houses is about 85%. About 7% of houses are townhouses, and the rest of them are apartments/condos. According to Fan *et al.* (2023), the vast majority of houses in Beijing are apartments with a similar floor plan in high buildings. In contrast to the Beijing housing market, the majority of houses in the sample are detached single-family houses, implying that the houses are relatively unique and heterogeneous. Also, the average home size is about 2,149 square feet, and the house has about three bedrooms and two bathrooms on average.

Table 3: Descriptive Statistics of Houses in the Sample

Variable	Percentage
Detached Single-Family Home	84.75
Townhouse	7.14
Apartment/Condo in building with +5 units	4.56
Apartment/Condo in 2 to 4 units	2.94
Cabin/Cottage	0.61

Variable	Mean	Sd	Min	P25	P50	P75	Max
Square Footage (in 1,000 sqft)	2.15	0.91	0.42	1.50	1.99	2.60	10.00
Number of Bedrooms	3.40	1.00	1.00	3.00	3.00	4.00	41.00
Number of Full Bathrooms	2.10	0.90	1.00	2.00	2.00	2.00	35.00

[10] Fan *et al.* (2023) and Merlo and Ortalo-Magne (2004) also present data showing that the listing prices are highly sticky in the England and Beijing housing markets.

In contrast to housing transaction data from the Multiple Listing Service, the NAR survey provides the demographic information of sellers. In Table 4, I present the descriptions of demographic information of the sellers in terms of single/couple, whether they have a child, age group, and race. Among the sellers in the sample, a majority of sellers were white, couple, and had a child or children. Also, the sellers in the sample were uniformly distributed among the age group between the 30's and 60's. Compared to Han and Strange (2014), the share of white are relatively high.[11] Because the data obtained by the survey and data periods are different, there is a possibility that the whites were oversampled in the survey.

Table 4: Descriptions of Demographics in the Sample

Characteristics	Percentage
Single	18.47
Couple	81.53

No child	39.08
Have a child or children	60.92

Age	Percentage	Race	Percentage
20 ~ 29	3.70	Black	1.45
30 ~ 39	23.77	Asian	2.42
40 ~ 49	18.07	White	93.35
50 ~ 59	19.90	Hispanic	1.89
60 ~ 69	23.19	Other	0.89
70 ~ 79	9.81		
over 80	1.56		

In Table 5, I describe the sellers' household income in the sample. The income distribution of the sellers in the sample follows a normal distribution, with approximately 40% of the sellers belonging to the income range of $85,000 to $150,000. These demographics and household income variations help me capture heterogeneities in sellers' waiting costs. In particular, single/couple and household income are essential pieces of information for computing the expected tax schedule for homeowners.

[11] According toHan and Strange (2014), approximately 73% of home sellers were white in 15 separate NAR surveys during 1987 ~ 2010.

Table 5: Description of Household Income ($ thousands) in the Sample

Household Income	Percentage	Household Income	Percentage
Less than 25	1.53	100 ~ 125	17.78
25 ~ 35	2.64	125 ~ 150	11.72
35 ~ 45	3.81	150 ~ 175	8.34
45 ~ 55	4.56	175 ~ 200	5.25
55 ~ 65	5.83	200 ~ 250	6.26
65 ~ 75	6.66	250 ~500	5.87
75 ~ 85	7.07	500 ~ 1000	0.84
85 - 100	11.60	More than 1000	0.26

2.2 Other data

I use the American Housing Survey (AHS) and American Community Survey (ACS) to obtain supplementary information about counties. For example, I acquire the housing inventory at the county level from the AHS and population, median income, and annual property taxes at the county level from the ACS. Also, the Individual Tax Statistics from the Internal Revenue Service (IRS) provides individuals' tax information based on individual Form 1040 income tax returns. While calculating the tax schedule, I rely on some information from the tax statistics, such as amounts of charitable giving. Last, I use the Housing Price Index from the Federal Housing Finance Agency (FHFA) to compute the median home value in dollars at the county level.

3 Model

To investigate a seller's listing price choice in response to changes in various types of tax provisions related to housing, I build and estimate a static model of home selling where the seller chooses the listing price to maximize his payoff. I take the seller's decision to sell a house as given because the data set only includes the houses that are listed and transacted. The model assumes payoff maximization by the seller given a known survival function for the time it takes to sell the house conditional on the listing price. The model also assumes that the seller does not revise his listing price because sellers do occasionally revise their listing price in the data.

There was a hurdle to model the seller's strategic choice and the buyer's side together, as previous empirical housing literature faced due to the lack of the buyer's side information. To consider the seller's home selling problem with the buyer's side, required at least some buyer-side information related to each seller's house transaction, such as the number of offers the seller received. For example, Merlo *et al.* (2015) use unique England housing data, including a negotiation process with transaction information, to consider the seller's listing price choice and selling decision problem.[12] To overcome the lack of adequate data, instead of explicitly modeling the buyer's behavior and negotiation process, I incorporate survival analysis into the payoff maximization problem of the seller. Thus, the buyer's side is exogenously given to the seller in a non-structural method, and the seller considers his strategic choice of listing price in the model. Also, the data I use allows me to incorporate a tax deduction benefit of owning the house in the model, which affects the seller's listing price decision.

The following sections explain the model in detail. First, in Section 3.1, I describe how hazard rate and survival function are built. In particular, I demonstrate how a tax deduction benefit for a homeowner is incorporated into a predicted market value of the seller's house. After that, in Section 3.2, I describe the seller's payoff maximization problem through the housing transaction. I explain how the sales price is determined and how the seller incurs a weekly waiting cost for the housing transaction.

3.1 Survival Analysis

3.1.1 Hazard Rate

I start with the hazard rate, which is jointly determined by the seller's listing price choice, the hedonic market value of the house, and other factors. The hazard rate is a conditional probability for selling the seller's house. It is the probability that the seller sells his house in week t given that the house has not sold prior to week t.

In the hazard rate, X_{ij} is the set of explanatory variables related to each regional market condition, P_{ij}^{l} is the seller i's original listing price, $\widehat{H_{ij}}$ is the log of the hedonic market valuation of the house through the hedonic regression, and D_{ij} is an interaction term between the median income in county j and the hedonic market valuation of the seller's house . Each seller in county j has the same county-specific random effect within a county, but each county has a different county-specific

[12] They do not explicitly build the model for the buyer's behavior in the search and and bargaining process. Instead, they calibrate the buyer's bid function to solve the seller's strategic choice.

random effect. Thus, the county-specific random effect $\nu_j \sim iidN\left(0, \delta_\nu^2\right)$ helps to capture the unobserved housing market heterogeneity across counties with observed variables. The house-specific error term ϵ_{ij} captures unobserved components that are not explained by the deterministic components of the hazard rate. I define the distribution of ϵ_{ij} later with other error terms in Section 3.2.

The baseline hazard $\kappa_0(t)$ is a piece-wise flat function, and I discretize the spline node points based on the distribution of the time on the market. Because half of the housing transaction occurs in the early weeks, I discretize the spline node points every week until week 5, and then each node point includes about 4~6 percent of samples in total observations. Meyer (1990) has shown that the estimated parameters in the model may be sensitive to how the distribution of the baseline hazard is specified. Thus, I use a semi-parametric specification for the baseline hazard. The hazard rate consists of the unspecified baseline hazard $\kappa_0(t)$ and the covariate part from the exponential function. This semi-parametric approach can help to estimate more consistent parameters for the model.

The hazard rate for seller i in county j is

$$\lambda_{ij}\left(t|U_{ij}, \nu_j, \epsilon_{ij}\right) = \kappa_0(t) exp\left\{U_{ij} + \nu_j + \epsilon_{ij}\right\} \tag{1}$$

where

$$U_{ij} = X_{ij}\beta + logp_{ij}^l\delta + \widehat{H_{ij}}\gamma + D_{ij}\beta_D \tag{2}$$

$$\kappa_0(t) = exp\left(\alpha_t\right). \tag{3}$$

The survival function is

$$S_{ij}\left(t|U_{ij}, \nu_j, \epsilon_{ij}\right) = exp\left\{-\int_0^t \lambda_{ij}\left(z|U_{ij}, \nu_j, \epsilon_{ij}\right) dz\right\}. \tag{4}$$

For simplicity, I suppress other variables and use $\lambda_{ij}\left(t|logP^l, \epsilon\right)$ and $S_{ij}\left(t|logP^l, \epsilon\right)$ below.

I describe explanatory variables related to each parameter in equation (2). County-related variables that influence the demand for houses in county j are included in X_{ij}. As Genesove and Han (2012) and Knight (2002) did, I consider the population and income of county j through the housing stock over the population and the log of the median income. The relative housing stock affects the supply of housing on the market. Higher income may indicate higher demand for high-quality houses that cost more. According to Anglin (2006), market condition changes can affect the probability of sales for the house. I try to capture the county-level market condition through the estimated median home value in dollars in county j.[13]

A high listing price p^l_{ij} decreases the hazard rate for the seller's house. To sell the house at the highest possible price, the seller can set a high listing price, but it takes more time on the market to find a potential home buyer who is willing to pay the high sales price. One may think that the seller has an incentive to choose a listing price at ∞. Suppose the seller sets the listing price at ∞. Because the sign of δ in equation (2) is expected to be negative, the survival function in equation (4) will be one, which means the house will not be sold in this case. Also, since the sales price is determined by the listing price in the model, the seller cannot choose a listing price at ∞.[14]

The third term $\widehat{H_{ij}}$ represents the log of the predicted market value of the seller's house through a hedonic regression.[15] As Knight (2002) did, I also examine the impact of market thickness on the hazard rate, albeit with a different approach.[16] I include an interaction term between the market valuation of the house through the hedonic regression and the median income in county j. The hazard rate depends upon the income distribution that can support the hedonic market value of the house in county j. Houses with higher hedonic market values tend to have higher listing prices, and they take longer to sell in towns where the proportion of low-income households is higher compared to other towns. Since there are fewer buyers who can afford expensive houses in such towns, the seller who wants to sell the expensive house needs to wait longer to be matched with a potential buyer.

[13] I compute the median home value in dollars. The details are in Appendix A.1.

[14] The details of the sales price determination process are discussed in Section 3.2

[15] The details of the hedonic regression are discussed in Section 3.1.2

[16] Knight (2002) considers the market thickness through dummy variables, which depend on the selling price level.

3.1.2 The Predicted Market Valuation of the Seller's House

I use a hedonic regression to compute the predicted market value of the seller's house. A house consists of many characteristics that affect its value. According to hedonic theory (Rosen, 1974), the value of a house is determined by the contribution of each of these characteristics, which include physical attributes and other relevant housing-related factors. Malpezzi (2003) summarizes that other relevant factors include locational aspects (city or suburb, access to amenities, etc.), neighborhood characteristics (public goods, school district, socio-economic factor of neighborhood, etc.), and various other attributes. Also, some literature (Zabel and Kiel, 2000; Kim *et al.*, 2003; Costa and Kahn, 2003) considers environmental characteristics. In this paper, I specifically consider the homeowner's tax deduction benefit as one of the house's characteristics because the tax deduction benefits related to housing can be capitalized into housing price.

I run the hedonic regression of the home's transaction price H_{ij} on the set of house characteristics Z_{ij} and the potential homeowner's tax deduction benefit of owning the house V_{ij}. The hedonic regression equation is

$$logH_{ij} = Z_{ij}\beta_Z + \omega V_{ij} + \eta_{ij} \tag{5}$$

where $\eta_{ij} \sim iidN(0, \sigma_\eta^2)$ reflects the unobserved value of the house for the potential homeowner that the seller cannot know. The explanatory variable Z_{ij} includes the square footage, number of bedrooms, number of bathrooms, county dummies, transaction year dummies, and short sale dummies. In equation (5), V_{ij} is an important explanatory variable in that it can capture the potential homeowner's tax deduction benefit changes from tax reform related to housing. When it occurs, the predicted market valuation of the seller's house in equation (1) is affected by the changes in V_{ij}. Thus, the hazard rate and survival function of the seller's house are affected simultaneously.

3.1.3 Potential Homeowner's Tax Deduction Benefits of the House

Homeowners can choose the itemized deduction or standard deduction depending on which option can give more deduction benefits to them. When a homeowner chooses the itemized deduction, he can benefit from owning the house through the mortgage interest deduction and property tax deduction. In the model, V_{ij} is the tax deduction benefit from owning a house when a potential homeowner owns the house. To compute V_{ij}, I need to know the potential homeowner's expected tax schedule first. I want to know the characteristics of the person who will buy and own the house, but it is almost impossible to observe it in available data. Instead, I use the present homeowner's characteristics as a proxy for the potential homeowner's characteristics. To own the same quality of house, the current seller and potential homeowner would share many characteristics regarding household income, wealth, and family composition. Therefore, the current seller's demographics would be a good proxy for the potential homeowner to calculate V_{ij}.

One can think that the neighborhood's average income can be a better proxy to compute the potential homeowner's tax deduction benefit of owning the house. However, there is a problem with using it as a proxy. Because the minimum geographic level is a county in the data, the average income of a county is not proper to compute the potential homeowner's tax deduction benefit of owning the house. Also, the housing prices and characteristics in the same neighborhood are heterogeneous even in the same county. The average income of a neighborhood may be related to the potential homeowner's income level. However, a neighborhood income level cannot represent a potential homeowner's characteristics better than the present homeowner's.

Let ID be an itemized deduction, and SD be a standard deduction. Denote $1(ID_{ij} > SD)$ as an indicator for a potential homeowner for whom it is worthwhile to choose the itemized deduction rather than the standard deduction. Property taxes are determined by the property tax rate and the assessed value of the house. The assessed value of the house can be obtained using two different methods. One is a market value assessment, and the house value is regularly updated to reflect changes in the market value. Another is an acquisition value assessment, which is based on its purchase price and remains stable over time. Since the acquisition value assessment is common in most states, I assume the level of assessment is 100 percent of the market value so that the sales price p^s_{ij} becomes the tax assessment value. Since not all counties' property tax rates are public information, I compute effective property tax rates from the Census Bureau's ACS.[17] Using the estimated effective property tax rates in the county, I compute the expected property taxes for the homeowners, which is $\tau^p_j p^s_{ij}$ and remains stable over time. The amounts of the expected

[17] I use the same methodology with the Tax Policy Center and the National Association of Home Builders. The details are in Appendix A.2

property taxes at the w_{ij}^{th} year from the house purchase is $\left[\tau_j^p p_{ij}^s\right]^{w_{ij}}$. Also, the amounts of the mortgage interest deduction at the w_{ij}^{th} year from the house purchase is $MI_{ij}^{w_{ij}}$. The estimated $MI_{ij}^{w_{ij}}$ is obtained from the calculation of the cumulative interest paid at the end of any period year. In Appendix B, I show the details of the tax schedule calculation. During the tax schedule calculation, I consider the alternative minimum tax together. To apply some changes in tax provisions in the counterfactual analyses, I modify some equations in the tax schedule calculation based on tax reform.

Given the tax schedule, expected property taxes, and amounts of the mortgage interest deduction at the w_{ij}^{th} year from the house purchase, the potential homeowner i's benefit of owning the house in county j due to the tax deduction is

$$V_{ij} = 1(ID_{ij} > SD) \times \tau_i \times \left\{ \sum_{w_{ij}=1}^{\infty} {\phi_v}^{w_{ij}-1} \left[\tau_j^p p_{ij}^s\right]^{w_{ij}} + \sum_{w_{ij}=1}^{30} \phi_v^{w_{ij}-1} MI_{ij}^{w_{ij}} \right\} \tag{6}$$

where τ_i is the marginal federal income tax rate of the potential homeowner i, and ϕ_v is the discount factor of the asset. I assume $\phi_v = 0.97$ based on the average of the 30-year treasury rate in 2017-18. Because the homeowner keeps paying property tax as long as she owns the house, I calculate this expense over an infinite horizon. However, in accordance with the model assumption, the potential homeowner is expected to complete the mortgage payments within 30 years. Therefore, I consider the mortgage interest deduction to be completed after this 30-year period.[18]

3.2 Payoff Maximization

Given a known survival function for the time it takes to sell the house conditional on the listing price, the seller wants to maximize the expected present value of payoff with respect to the listing price. Thus, the listing price affects the probability of selling the house and time on the market. The seller incurs a waiting cost of not selling the house, c_{ij}, every week while the seller's house is on the market. The weekly waiting cost is a function of the seller's demographics G and the error term ζ_{ij}. The error term reflects other unobserved variables from the seller's demographics that can affect the seller's waiting cost. Also, the listing price and time on the market affect the sales

[18]It may not be unreasonable to assume that w_{ij} can go up to ∞ for the sum of $MI_{ij}^{w_{ij}}$ in equation (6). If so, it allows for the case that the house can be sold to another buyer or the mortgage can be refinanced before 30 years.

price of the house through a sales price determination function. The details are discussed below.

I assume the seller knows the hazard rate of the house for the time to sell, conditional on his listing price. Because most of sellers in the data did not change their listing price, I assume that the seller does not revise the listing price after listing the house on the market. Denote Π_{ij} as the seller i's expected present value of the payoff from the house transaction in county j. When the seller i lists his house on the market in county j, he chooses the listing price to solve

$$\begin{aligned} E\max_{p^l_{ij}} \Pi_{ij} = & \int_0^\infty e^{-\rho z} \left[S_{ij} \left(z | logp^l, \epsilon \right) \lambda_{ij} \left(z | logp^l, \epsilon \right) p^s_{ij} \left(logp^l, \varsigma \right) \right] dz \\ & - \int_0^\infty e^{-\rho z} \left[S_{ij} \left(z | logp^l, \epsilon \right) c_{ij} \left(G, \zeta \right) \right] dz \end{aligned} \tag{7}$$

where

$$logp^s_{ij} = (1 - \phi t)\, logp^l_{ij} + \varsigma_{ij} \tag{8}$$

$$c_{ij} = G_{ij}\psi + \zeta_{ij}. \tag{9}$$

The error term ϵ_{ij} is independent over houses, counties, and it is not correlated with the county-specific random effect ν_j in equation (1). The three error terms $\begin{pmatrix} \varsigma_{ij} \\ \epsilon_{ij} \\ \zeta_{ij} \end{pmatrix} \sim iidN(\mu, \Sigma)$.

I incorporate three features in this payoff maximization problem. First, I consider the trade-off between the listing price and time on the market. As Miller and Sklarz (1987), Yavas and Yang (1995), and Anglin *et al.* (2003) noted, a higher listing price leads to longer time on the market. Because the sign of δ is expected to be a negative in equation (1), a higher listing price eventually decreases the probability of selling the house compared to a lower listing price, which leads to spending more time on the market.

Second, I consider the relationships between the time on the market, home quality, and sales price. I add the discounting factor ϕ in the sales price determination function, which discounts the sales price from the listing price as the house spends more time on the market. Fan *et al.* (2023) show the relationship between house quality learning by buyers and willingness to pay for a home. When the house is unsold and spends more time on the market, the buyer can expect that the house has a lower quality than other comparables. In this case, the time on the market can be a signal of home quality to buyers. Thus, the sales price can be lower as the time on the market increases. The first and second features imply that the seller's choice of the listing price is closely related to the time on the market and sales price for the house.

Last, as in Albrecht *et al.* (2016), Merlo *et al.* (2015), and Fan *et al.* (2023), I consider that the sales price can be higher than, equal to, or lower than the listing price. In order to maximize the seller's payoff, the sales price, along with the time on the market, is crucial to the seller. In a specific market period, the seller should try to sell his house at the highest possible sales price. In equation (8), the sales price is mainly determined by the listing price, but it is discounted by ϕt depending on how many weeks the house spends on the market. This captures the effect that the potential buyer's willingness to pay decreases as the time on the market increases. [19] Also, I allow for the case where the seller sells his house above the listing price.[20] When the seller receives a positive shock ς_{ij} while selling the house, he can sell it at higher than his listing price.[21]

4 Estimation Strategy

4.1 The Likelihood Function

I denote θ as the set of parameters to be estimated. Denote $b_i = 1$ as the seller i's time on the market is right-censored. As I have described in Section 2.1, I am not sure whether the seller's time on the market was precisely 99 weeks or more than 99 weeks for the sellers who responded their time on the market was 99 weeks. However, I know they finally sold their houses by observing their listing and sales prices. The dependent variables of the likelihood function are the listing price p^l, sales prices p^s, and waiting time t.

[19] Miller and Sklarz (1987) showed that an overpriced house can be sold at a better sales price. When the seller sets a high listing price, he can be matched with a buyer who gives a high value to the seller's house while spending more time on the market. After the matching, the seller can sell his house at the listing price or below the listing price through a negotiation process with the buyer.

[20] According to Han and Strange (2014), the share of housing transactions above listing price has grown since the 2000s housing boom. In terms of the seller's strategic choice, the seller can choose a lower listing price to attract many buyers at the same time, which leads to a bidding war among the buyers.

[21] The seller cannot choose the situation he wants but can influence the matching and time on the market through his strategic choice. Due to data limitations, it is impossible to identify whether the sales price is determined through a one-to-one negotiation process or a bidding war among buyers.

The seller $i's$ likelihood contribution of the house in county j is

$$\mathcal{L}_{ij}\left(\theta|p^l, p^s, t^*, \nu_j\right) = \left\{f_{p^l}\left(p^l\right) \cdot f_{p^s}\left(p^s|p^l, t^*\right) \cdot f_t\left(t^*\right)\right\}^{(1-b_i)} \\ \times \left\{f_{p^l}\left(p^l\right) \cdot f_{p^s}\left(p^s|p^l, t^*\right) \cdot S_{ij}\left(t^* = 99|p^l, \epsilon\right)\right\}^{b_i} \quad (10)$$

which is conditional on the actual listing price, sales price, time-on-market t^* in the data, and the county-specific random effect ν_j. Because the seller $i's$ likelihood contribution of the house in county j is conditional on ν_j, I need to integrate ν_j to compute the county $j's$ likelihood contribution. Thus, the county $j's$ likelihood contribution is

$$\mathcal{L}_j(\theta) = \int_\nu \left\{\prod_{i=1}^{I_j} \mathcal{L}_{ij}\left(\theta|p^l, p^s, t^*, \nu_j\right)\right\} f_\nu(\nu_j)\, d\nu_j \quad (11)$$

where I_j is the number of the sellers in county j. The final form of the likelihood function is a sum of the log-likelihood contributions of each county j,

$$log\mathcal{L}(\theta) = \sum_{j=1}^{J} log\mathcal{L}_j(\theta). \quad (12)$$

4.2 Estimation

I estimate the model parameters using Maximum Simulated Likelihood (MSL). According to Börsch-Supan and Hajivassiliou (1993), MSL estimates perform nicely with enough number of draws and a good simulation method. To evaluate the likelihood contributions using simulation, I compute $\tilde{\varsigma}_{ij}$ from the data directly using the sales price determination function in equation (8). Then, I simulate ϵ^r_{ij} conditional on $\tilde{\varsigma}_{ij}$, and also simulate ν^r_j. Given $\tilde{\varsigma}_{ij}$, simulated ϵ^r_{ij}, and simulated ν^r_j, I solve for ζ_{ij} which satisfies the first order condition of the payoff function in equation (7). Using these solutions of error terms $\left\{\tilde{\varsigma}_{ij}, \tilde{\epsilon}^r_{ij}, \tilde{\zeta}_{ij}\right\}$, I evaluate the likelihood contributions and estimate the model parameters that maximize the log-likelihood function. As Geweke (1988) and Stern (1997) show, I use antithetic acceleration to reduce the simulation error. In Appendix C, I show the details of evaluating the log-likelihood function.

5 Estimation Results

5.1 Hazard Rate Parameters

Table 6 shows the estimates of the hazard rate specified in equation (1). The interpretation of the hazard rate parameter is similar with the log-log case of a linear regression equation. For the log of listing price in the hazard rate, a 1% increase in the listing price of the seller's house leads to a 1.049% decrease in the hazard rate of the seller's house. The sign for the parameter of the listing price is negative. Thus, a high listing price decreases the probability of sales of the house in week t conditional on the house not having sold prior to week t.

Also, the predicted market value of the seller's house affects the hazard rate in a predicted way. A high predicted market value of the house increases the hazard rate of the seller's house depending on the log of median income in the county. A 1% increase in the predicted market value of the seller's house leads to a $\{0.311 - 0.107 \times \log(\text{median income})\}\%$ increase in the hazard rate. Depending on the size of median income in county j, a 1% increase in the predicted market value of the seller's house leads to a greater, less than, or equal to 0.311% increase in the hazard rate. For example, consider a county where the median income is \$80,000. A 1% increase in the predicted market value of the seller's house leads to a 0.335% increase in the hazard rate. In contrast, if the median income in a county is \$200,000, the effect of that is a 0.237% increase in the hazard rate.

For the explanatory variables related to each regional market condition, a greater estimated median home value and greater relative housing stock are associated with a lower hazard rate, although the latter variable is not significant. The effect of the median income in a county on the hazard rate of the seller's house depends on the predicted market value of the house. A 1% increase in a county's median income leads to a $\{0.238 - 0.107 \times \log(\text{predicted market value of the house})\}\%$ increase in the hazard rate. As the predicted market value of the seller's house increases, the effect of county median income on the hazard rate is weaker but keeps having a positive effect on the hazard rate until the predicted market value is about \$1 million.

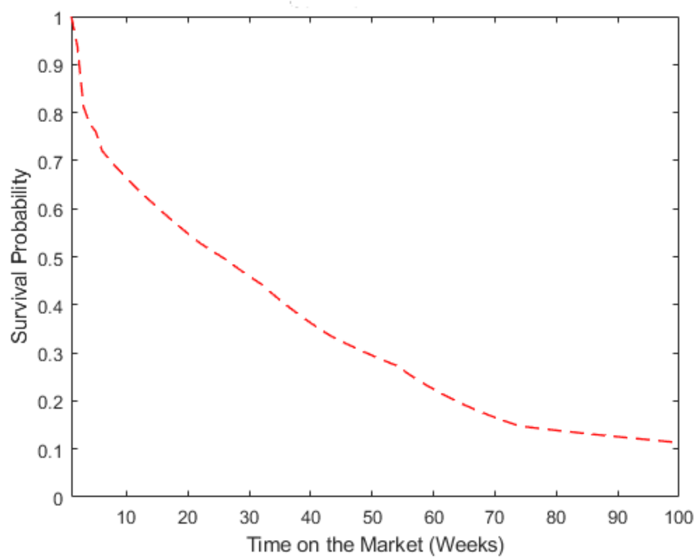
Table 6: Parameter Estimates: Hazard Rate (Dollar unit: $100,000)

		Estimate	Standard error
Baseline Hazard			
Week 1	α_1	-2.067 ***	(0.082)
Week 2	α_2	-1.188 ***	(0.083)
Week 3	α_3	-2.341 ***	(0.088)
Week 4	α_4	-2.986 ***	(0.095)
Week 5	α_5	-2.110 ***	(0.091)
Week 6∼7	α_6	-2.985 ***	(0.092)
Week 8∼9	α_7	-3.059 ***	(0.092)
Week 10∼11	α_8	-2.994 ***	(0.098)
Week 12∼13	α_9	-3.084 ***	(0.091)
Week 14∼17	α_{10}	-3.019 ***	(0.095)
Week 18∼21	α_{11}	-3.000 ***	(0.100)
Week 22∼25	α_{12}	-3.148 ***	(0.104)
Week 26∼31	α_{13}	-2.932 ***	(0.101)
Week 32∼42	α_{14}	-2.585 ***	(0.101)
Week 43∼53	α_{15}	-2.757 ***	(0.114)
Week 54∼73	α_{16}	-2.139 ***	(0.108)
Week 74∼93	α_{17}	-3.123 ***	(0.152)
Week 94∼99	α_{18}	-3.044 ***	(0.368)
Hazard Rate			
Log of listing price	δ	-1.049 ***	(0.013)
Log of the predicted market value of the seller's house	γ	0.311 ***	(0.021)
Housing stock over the population	β_1	-0.065	(0.049)
Log of the median income	β_2	0.238 ***	(0.026)
Log of the estimated median home value	β_3	-0.100 ***	(0.010)
Log of the median income × Log of the predicted market value of the seller's house	β_D	-0.107 ***	(0.022)

*** 0.01, ** 0.05, * 0.10

Using the hazard rate estimates, I plot the survival function. Figure 3 presents the average value of the survival function of each seller over the time on the market. Due to the covariate part in equation (1), the survival function differs for each seller.

Figure 3: Survival Function



5.2 Payoff Function Parameters

In Table 7, I presents the estimates of the payoff function specified in equations (7), (8), and (9). The seller's expected payoff is discounted by about 1% every week in equation (7). One may think this discount rate is too large. Considering the fact that the average time on the market is about 13 weeks and most sellers sold their house in 33 weeks, this discounting factor for payoff per week seems reasonable. I have another discounting factor ϕ in equation (8), which is different than the regular discount factor ρ. The sales price discounting factor ϕ represents how much the potential buyer's willingness to pay decreases as a function of time on the market and listing price when the sales price is determined. A positive estimate of the sales price discounting factor per week implies that the sales price decreases as the time on the market increases.

For the waiting cost, the base group is a white couple with a child or children under 18. The estimate of the waiting cost constant implies the waiting cost per week does not vary much across marital status, race, age, and income level. However, the seller who is single or does not have a child has a lower waiting cost, although the estimate of single is not significant. As household income increases, the waiting cost per week also tends to increase. The estimation implies that the average waiting cost per week is about \$6,860. Considering the facts I discussed in the previous paragraph, the waiting cost per week does not seem too large either. Merlo *et al.* (2015) also considered the holding cost for the seller, but it was not a significant estimator and their definition of holding cost are different with mine. Thus, it may not proper to compare those two results.[22] The standard deviation of ν is quite large and it is greater than the standard deviation of ϵ, which implies that the heterogeneity across counties should be considered in the model.

Table 7: Parameter Estimates: Payoff Function

		Estimate	Standard error
Discounting Factor			
Sales price discounting factor per week	ϕ	0.0014 ***	(0.00004)
Payoff discounting factor per week	ρ	0.0096 *	(0.0050)
Waiting Cost (Dollar unit: $100,000)			
Waiting cost constant	c_0	0.0677 ***	(0.0027)
Single	c_1	-0.0037	(0.0026)
No Child	c_2	-0.0047 *	(0.0027)
Black	c_3	-0.0036	(0.0048)
Asian	c_4	-0.0049	(0.0043)
Hispanic	c_5	-0.0051	(0.0045)
Other	c_6	-0.0051	(0.0065)
(Age/100)	c_{age}	0.0074	(0.0116)
(Age/100) squared	c_{agesq}	0.0012	(0.0162)
Log of household income	c_{hhinc}	0.0062 ***	(0.0017)
Error Terms			
Correlation between ϵ and ς	ψ	0.4282 ***	(0.0086)
Standard deviation of ϵ	σ_ϵ	0.3780 ***	(0.0065)
Standard deviation of ν	δ_ν	0.4365 ***	(0.0124)

*** 0.01, ** 0.05, * 0.10

5.3 Goodness-of-Fit

I use a local linear kernel regression estimator to check the goodness-of-fit of the model. It shows how well the model dependent variables fit the actual data: listing price, sales price, and time on the market. The further the kernel red line diverges from the 45-degree blue line, the less effective the model is at explaining the data.

[22] Merlo *et al.* (2015) defined the holding cost as the cost associated with maintaining the house in a clean state and being prepared to leave it on short notice for real estate agents to present it to potential buyers.

Figure 4: Sample Fit: Listing and Sales Price

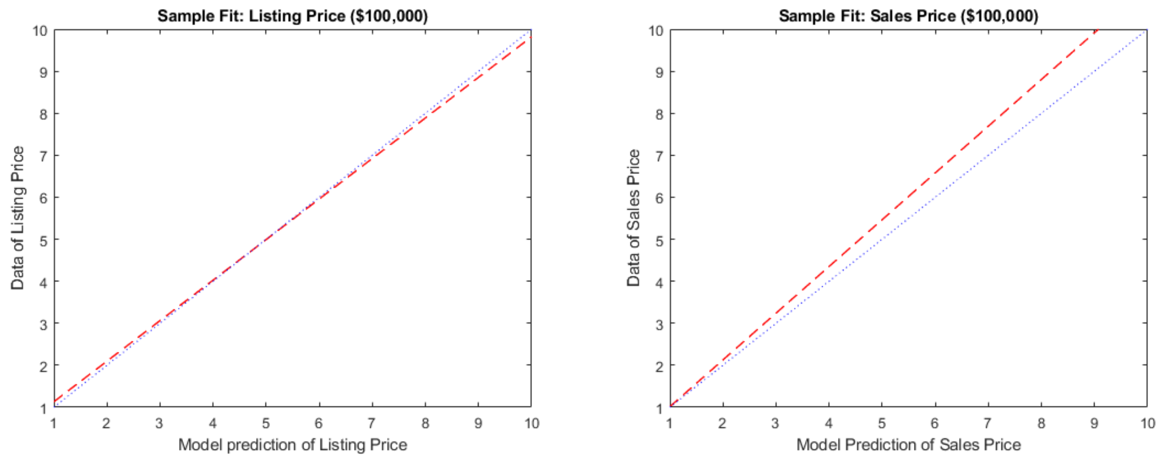


Figure 5: Sample Fit: Time on the Market

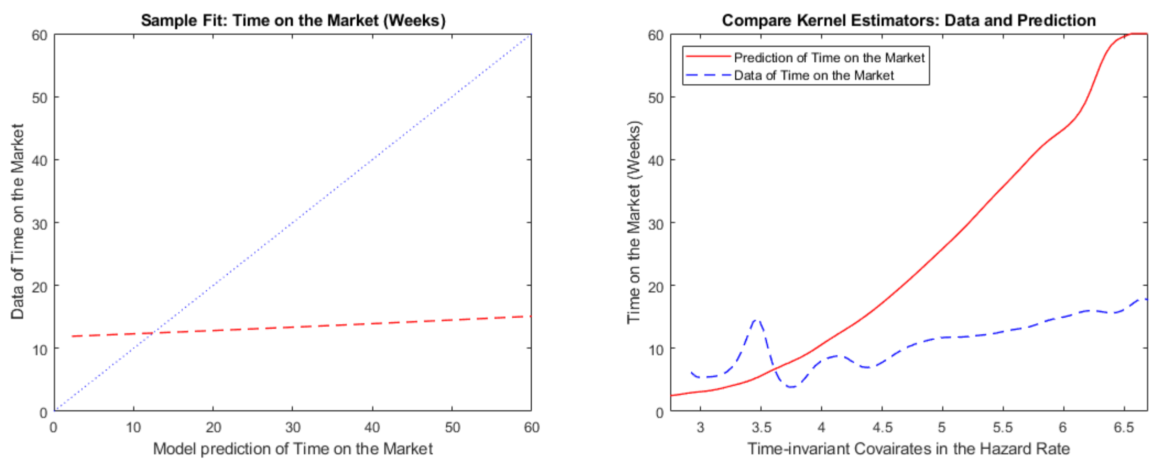


Figure 4 and 5 represent the sample fit of listing price, sales price, and time on the market. While the listing and sales price show excellent fits, the time on the market is somewhat overpredicted. I compare kernel estimators of actual data time on the market and model prediction of time on the market. This difference makes the time on the market overpredicted. This is due to the fact that the distribution of the error terms in the hazard rate is quite large, which means the existence of the unobservables can explain the difference between the two kernel estimators. Another reason can be the lack of buyer-side information related to each seller's house transaction. Merlo *et al.* (2015) and Fan *et al.* (2023) predict the time on the market well. This may be due to the fact that Merlo *et al.* (2015) have buyer-side offers made on the house until the final sale, and Fan *et al.* (2023) have the number of home viewings with the transaction information.

6 Counterfactual Analyses

In this section, I use the estimated parameters to conduct counterfactual experiments. I evaluate the impact of tax reform related to housing on the seller's behavior and market outcomes in three different scenarios. Each scenario affects the potential homeowner's tax schedule and tax deduction benefit of owning the house V_{ij} in equation (5). I compute the potential homeowner's tax schedule and tax deduction benefit of owning the house V_{ij} after applying the changes in tax provisions.[23] Thus, each simulation produces a different distribution of the listing price, which leads to a different distribution of the sales price and time on the market.

Table 8: Bills Related to the SALT Deduction in the 118th Congress

#	Bill Title	Changes (Single / Joint return)
1	SALT Deductibility Act	Eliminate the current cap
2	Supporting Americans with Lower Taxes Act	Eliminate the current cap for a taxpayer whose income is below $400,000
3	TCJA Permanency Act	Make the TCJA permanent.
4	SALT Marriage Penalty Elimination Act	Increase the cap to $20,000 only for a joint return
5	SALT Relief Act	Increase the current cap to $50,000/$100,000
6	SALT Fairness and Deficit Reduction Act	Increase the current cap to $60,000/$120,000
7	Tax Relief for Middle Class Families Act	Increase the current cap to $100,000/$200,000

Table 8 summarizes the recent bills related to the SALT deduction introduced in the 118th Congress. I estimate the model parameters based on the tax regime before the TCJA. I do not conduct counterfactual experiments for the SALT Deductibility Act and the Supporting Americans with Lower Taxes Act. This is because these outcomes are expected to be similar to current model prediction outcomes. Thus, I do counterfactual analyses about the rest of the bills in Section 6.1 and 6.2. Also, I include another policy discussion about the mortgage interest deduction (MID).

[23] The details about this calculation are in Appendix B.2.

I evaluate the impact of reforming the MID in Section 6.3. Although I model the buyer's side in a simple, non-structural way, the counterfactual results correspond with the conclusions found in the relevant literature related to the general equilibrium model.

6.1 Effect of the TCJA

In this counterfactual experiment, I evaluate the impact of the TCJA and the TCJA Permanency Act on the seller's behavior and market outcomes. As discussed in Section 1, the TCJA reduced the incentive for homeowners to choose the itemized deduction rather than the standard deduction. This is because it decreased the tax deduction benefit related to housing, primarily through the SALT cap, and doubled the amounts of standard deduction for all taxpayers. Homeowners who change their tax schedule from the itemized deduction to the standard deduction cannot get any tax deduction benefit related to housing. In this case, they do not take into account the benefit of the tax deduction related to housing when they evaluate their housing market value. Homeowners who still choose the itemized deduction after the TCJA get a smaller tax deduction benefit related to housing, which makes them reduce their housing market value.

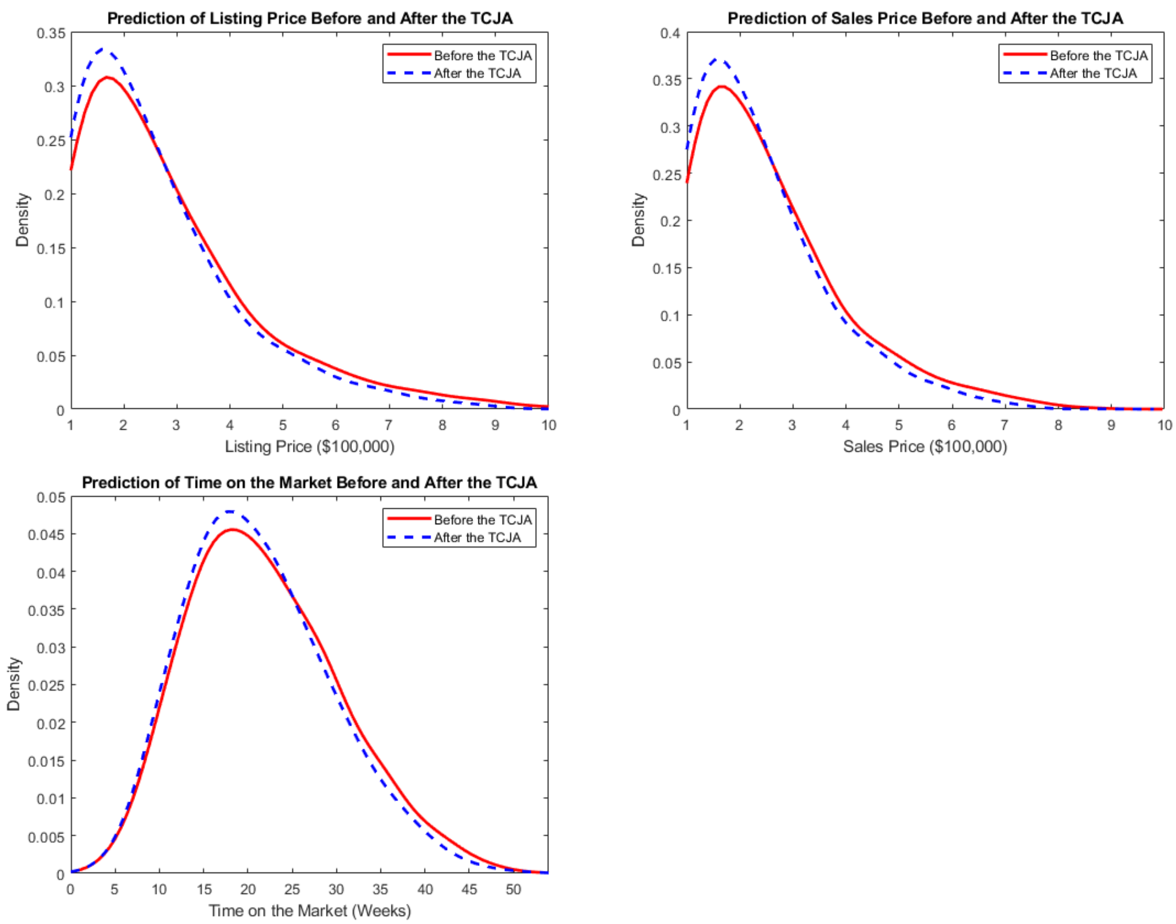
The TCJA decreases the tax deduction benefit related to housing, making housing less valuable. Thus, it affects the seller's listing price decision when he sells the house. Table 9 shows that the seller tends to post a lower listing price to sell his house, and the sales price also decreases after the TCJA. The seller chooses a listing price 7.38% lower, and the sales price decreases by approximately 7.30% on average after the TCJA provisions are applied. The time on the market decreases by about one week because the seller sets the lower listing price, which is an expected effect from the model.

In addition, I compare the densities of the listing price, sales price, and time on the market in Figure 6. Because the seller tends to choose a lower listing price, the distributions of the listing price, sales price, and time on the market move to the left. The densities of the listing price and sales price below about $300,000 rise, which implies housing value decreases on average. The density of time on the market between 15 weeks to 25 weeks increases as the density of high listing prices decreases.

Table 9: Simulation: Effect of the TCJA

	Listing Price ($ thousands)	Sales Price ($ thousands)	Time on the Market (weeks)
Before the TCJA (Benchmark)	275.05	253.13	21.94
After the TCJA	254.76	234.65	21.18

Figure 6: Simulation: Effect of the TCJA on Market Outcomes



This counterfactual result is consistent with other findings in the literature (Martin, 2018; Rappoport, 2019; Sommer and Sullivan, 2021). As less heterogeneity in the housing market is considered, the impact of the TCJA seems to be smaller magnitude on the housing price. Using the user cost model to simulate price changes, Martin (2018) found the average price effect of the TCJA is about -5.7%, with much variation in local impact. Rappoport (2019) focused on regional house price effects through the housing market clearing condition. His study revealed that house prices could decrease by approximately 2% on average and up to 7% depending on metropolitan areas. Sommer and Sullivan (2021) found the housing price at equilibrium decreased after the TCJA, but the effect was marginal. In the interest of tractability, their model dropped the source of heterogeneity, such as regional variation in housing prices and property tax rates.

The impact of the TCJA on the housing price in this paper is similar to other literature, and the only difference is the magnitude of the impact. Since I do not account for the general equilibrium effects, the counterfactual market outcomes are not affected by changes in the homeownership or rental housing market. When the general equilibrium effects are considered, it allows individuals in the economy to be homeowners or renters in the model. For example, suppose the effect of lowering the listing price on housing demand is greater than the effect of selling the house to be a renter on housing supply. In that case, the decrease in housing prices can be smaller. I believe this is the reason that the impact of the TCJA on housing prices in Rappoport (2019) and Sommer and Sullivan (2021) is smaller than what my model predicts by the counterfactual analysis. In contrast to Rappoport (2019) and Sommer and Sullivan (2021) which deal with the general equilibrium effect, this paper includes many sources of heterogeneity. Also, this counterfactual result provides important information about the housing market outcomes, such as listing price and time on the market, after the TCJA is implemented.

The counterfactual experiment results reported in Table 10 show that the effect of the TCJA on the market outcomes differs by the household income level and amounts of the property tax. Li and Yu (2022) used a difference-in-difference approach and showed a similar result that, depending on the property taxes, the effects of TCJA on the housing price growth rate vary across geographical regions. Table 10 presents the percentage change in market outcomes caused by the TCJA. High income households and high property tax payers are affected the most by the TCJA. In detail, the sellers in the 4th income quartile reduce the listing price by approximately 14.17%, and those in the 4th property tax quartile reduce the listing price by approximately 10.66%. Also, their house sales prices and time on the market for the house also decrease the most. These results are mainly due to the $10,000 SALT cap in the TCJA. The TCJA has a similar effect on other quartiles of income and property taxes. In other quartile groups, I find a decrease in their listing and sales prices by approximately 4% to 6%, which leads to a reduction in the time on the market, ranging from 0.20% to 2.08%. As the order of these quartiles increases, the impact of the TCJA is greater.

Table 10: Simulation: Effect of the TCJA on % Change in Market Outcomes

	Income Quartile			
% Change in	1st	2nd	3rd	4th
Listing Price ($ thousands)	-4.53	-5.10	-5.50	-14.17
Sales Price ($ thousands)	-4.48	-5.06	-5.94	-14.01
Time on the Market (weeks)	-0.20	-0.97	-0.91	-6.65

	Property Tax Quartile			
% Change in	1st	2nd	3rd	4th
Listing Price ($ thousands)	-4.87	-5.07	-6.20	-10.66
Sales Price ($ thousands)	-4.88	-5.00	-6.16	-10.55
Time on the Market (weeks)	-0.19	-1.03	-2.08	-4.08

6.2 Effect of Adjusting the SALT Cap under the TCJA

The TCJA has sunset tax provisions, which expire in 2025. After the passage of the TCJA, however, some legislators who represent high-tax states tried to increase the SALT cap. In 2021, the House eventually passed a bill for increasing the SALT cap to $80,000, but it was turned down in the Senate. During the 118th Congress, several bills related to increasing the SALT deduction cap were introduced again. Based on the introduced bills in Table 8, I do counterfactual experiments with three cases: SALT Marriage Penalty Elimination Act, SALT Relief Act, and Tax Relief for Middle Class Families Act. Based on three cases, I increase the SALT deduction cap to three different limits: $10,000/$20,000 for single and joint return cases; $50,000/$100,000 for single and joint return cases; $100,000/$200,000 for single and joint return cases.

Table 11: Simulation: Effect of Adjusting the SALT Cap under the TCJA

	Listing Price ($ thousands)	Sales Price ($ thousands)	Time on the Market (weeks)
After the TCJA (Benchmark)	254.76	234.65	21.18
SALT Marriage Penalty Elimination Act	263.10	242.11	21.42
SALT Relief Act	267.00	245.48	21.57
Tax Relief for Middle Class Families Act	267.09	245.57	21.59

Table 11 shows the effect of adjusting the SALT cap after the TCJA is implemented. Treat the counterfactual result in section 6.1 as a benchmark to compare the effect of adjusting the SALT cap. As the SALT cap increases, the market outcomes revert to those of the tax regime before the TCJA is implemented. However, they do not fully return to the exact levels of the pre-TCJA tax regime because the standard deduction is still doubled after the passage of the TCJA. When the SALT cap increases, sellers capitalize the tax deduction benefit related to housing into their housing market value. Thus, the sellers increase their listing prices, leading to higher sales prices and longer time on the market. Based on the counterfactual experiments, there is no significant difference in market outcomes by increasing the SALT cap from $50,000/$100,000 to $100,000/$200,000 for single and joint return cases.

Table 12: Simulation: Effect of Adjusting the SALT on % Change in Market Outcomes

	Income Quartile			
% Change in	1st	2nd	3rd	4th
Listing Price ($ thousands)	0.07	1.54	3.61	14.22
Sales Price ($ thousands)	0.07	1.52	3.57	14.04
Time on the Market (weeks)	0.03	0.74	1.71	6.71
	Property Tax Quartile			
% Change in	1st	2nd	3rd	4th
Listing Price ($ thousands)	0.51	1.55	3.39	9.65
Sales Price ($ thousands)	0.51	1.54	3.35	9.51
Time on the Market (weeks)	0.25	0.74	1.69	4.46

* Tax Relief for Middle Class Families Act

Table 12 presents the percentage changes in the listing price, sales price, and time on the market after applying the Tax Relief for Middle Class Families Act, compared to the market outcomes under the TCJA. All sellers in the sample increase their listing prices, resulting in higher sales prices and longer time on the market. In particular, sellers in the 4th income quartile and the 4th property tax quartile, who are the most significantly impacted by the TCJA, tend to increase their listing prices more than those in other quartiles. Consequently, this leads to the greatest increase in sales price and time on the market compared to the other quartiles. As the quartiles ascend, the impact of adjusting the SALT limit under the tax regime of the TCJA becomes more pronounced.

6.3 Effect of Eliminating the MID

The MID was built to encourage homeownership in the United States. Economists and policy analysts have long debated the effectiveness of the MID on homeownership. Also, the MID is a substantial fiscal burden to the government. At this point, it is interesting to consider how the seller's behavior and market outcomes change when there is no MID.

I conduct a counterfactual analysis assuming that the TCJA has expired. Table 13 shows the seller chooses their listing price approximately 16.43% lower than the benchmark when the MID is no longer available. Also, the sales prices decrease by approximately 16.34%, and time on the market decreases by about two weeks on average. This indicates that removing the MID significantly reduces the tax deduction benefit associated with housing, thereby diminishing the value of houses.

In Figure 7, I compare the densities of the listing price, sales price, and time on the market. In contrast to the scenario with the MID, sellers choose lower listing prices, resulting in a leftward shift in the distributions of listing price, sales price, and time spent on the market. The densities of listing prices and sales prices below $250,000 notably increase, suggesting an overall decrease in housing values. Moreover, there is an increase in the density of time on the market below 20 weeks as the density of listing prices over $250,000 decreases.

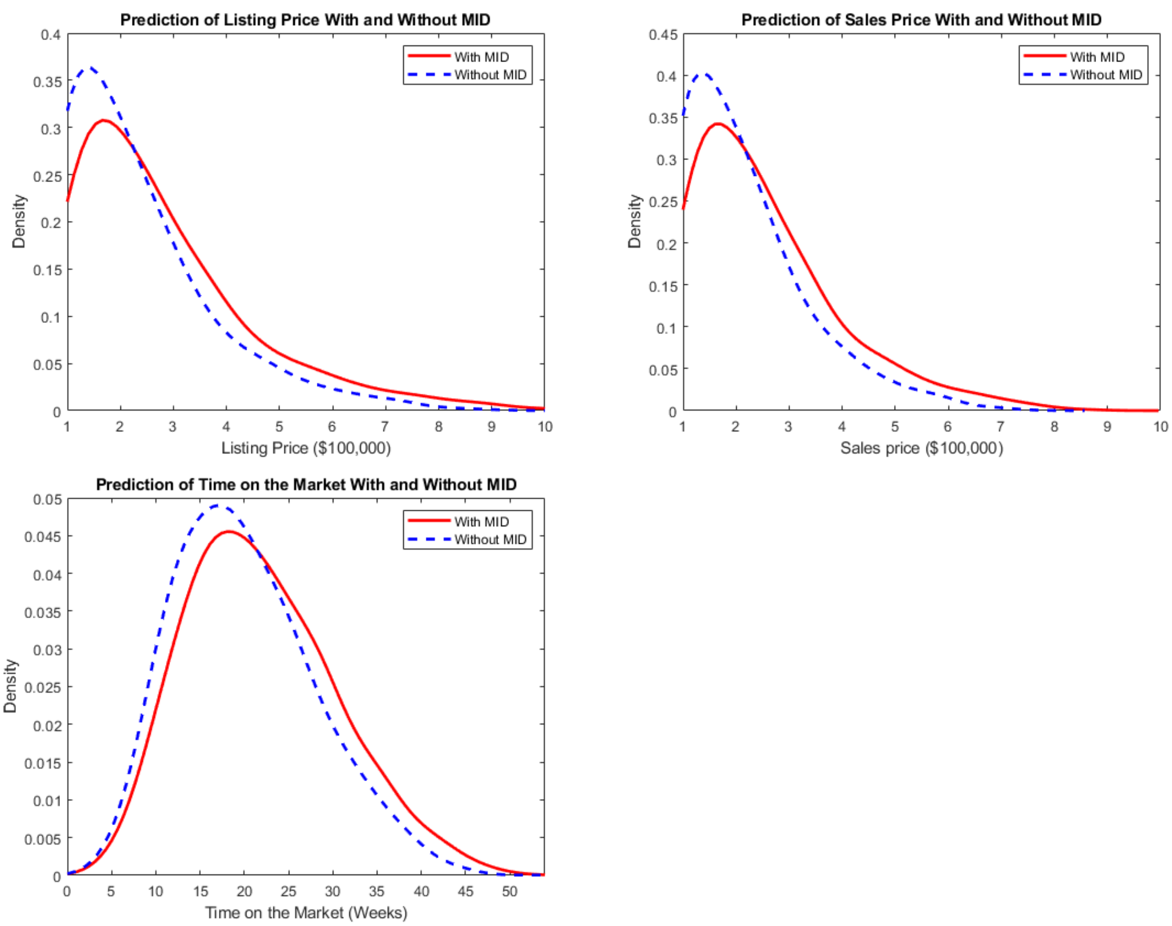
This counterfactual result is consistent with Sommer and Sullivan (2018), Davis (2019), and Rappoport (2017), but it shows that the impact of removing the MID is somewhat greater than what other literature found. According to Sommer and Sullivan (2018), when the MID is eliminated, the house prices at the equilibrium decrease by 4.2%. Davis (2019) found that house prices increase by 0.9% to 1.3% when the tax rate applied to mortgage interest rises by 1%. Using the housing market clearing condition, Rappoport (2017) presented that house prices would decline by 6.9% on average and up to 9.8% when the MID is unavailable.

Compared to other literature, the difference in the magnitude of the results from my counterfactual analysis may arise for two reasons. First, because I do not account for the general equilibrium effects in the model, the magnitude of the impact can be large due to the same reason discussed in Section 6.1. Second, I include more heterogeneity of the home sellers in the model by computing each seller's mortgage interest payment per year. If I incorporate the general equilibrium effects into the model, the impact of eliminating the MID on the listing price can be smaller than my counterfactual result. Consequently, this results in a diminished effect on both the sales price and time on the market.

Table 13: Simulation: Effect of Eliminating the MID

	Listing Price ($ thousands)	Sales Price ($ thousands)	Time on the Market (weeks)
Before the TCJA (Benchmark)	275.05	253.13	21.94
No MID	229.85	211.77	20.02

Figure 7: Simulation: Effect of the Eliminating MID on Market Outcomes



7 Conclusion

This paper is motivated by the recent tax reform, known as the Tax Cuts and Jobs Act, and the fact that tax deduction benefits related to housing can be capitalized into a housing price. To investigate the seller's listing price choice in response to changes in various types of tax provisions related to housing, I present a model of choosing a listing price by a seller who maximizes his payoff from the housing transaction, assuming that he knows a survival function for the time it takes to sell the house, conditional on his listing price. I do not explicitly model a buyer's behavior and bargaining process that results in housing transaction. Instead, I incorporate these features by combining the hazard rate with the model that focuses on the seller's payoff maximization. The hazard rate is affected by the seller's listing price choice and the predicted market value of the house. This predicted market value can change due to the estimated tax deduction benefit associated with housing, which in turn depends on the tax provisions.

Using the estimated model, I quantify the effect of the TCJA on the seller's listing price and relevant market outcomes. My findings indicate that, as a result of the TCJA, sellers tend to choose a listing price that is roughly 7.38% lower. This leads to an approximately 7.30% reduction in the sales price and reduces the time on the market by about one week. This is because sellers incorporate the reduced tax deduction benefit related to housing into their housing market value. High income households and those who pay high property taxes are mostly impacted by the TCJA.

In addition, in light of the bill introduced in the 118th Congress, I assess the effect of adjusting the SALT cap under the tax regime of the TCJA on the seller's listing price and relevant market outcomes by increasing the SALT deduction limit in three different scenarios. Based on the model projection, both the listing price and market outcomes tend to revert to levels closer to those predicted results of the pre-TCJA tax regime as the SALT cap increases. Furthermore, the high income households and households paying high property taxes, who are most impacted by the TCJA, increase their listing prices the most, resulting in the most increase in their sales price and time on the market compared to others.

Finally, I assess the impact of eliminating the MID on the seller's listing price and relevant market outcomes, assuming that the TCJA has expired. A counterfactual simulation suggests that the seller chooses their listing price approximately 16.43% lower, resulting in approximately

16.34% lower sales price and spending about two more weeks on average when the MID is no longer available.

A caveat related to this model should be made. Home selling problems for households and how sellers capitalize benefits associated with housing into their housing prices are important issues. Still, they are rarely studied, mainly due to the lack of adequate data that does not include both the sellers' and buyers' information. To overcome this data limitation, I make a strong assumption that the hazard rate provides a reasonable approximation of the buyer's behavior and the competition among the sellers in the county-level housing market. Relying on the survival analysis method, I can investigate the seller's listing price choice and waiting cost. Also, this framework allows me to study how sellers incorporate the capitalization effect of housing-related benefits, such as the tax deduction benefit associated with housing or neighborhood effect, on housing value to research the seller's listing price choice and market outcomes.

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Appendix A

Appendix A.1

The estimated effective property tax rates in county *j*

Since not all counties' real estate tax rates are public information, I compute the estimated effective property tax rates. As Harris *et al.* (2013) and Siniavskaia (2016) did, I use the American Community Survey (ACS). To obtain tax rate estimates for small sample counties, I use the five-year ACS data, which provide data for almost all US counties. Homeowners in the ACS responded with their home value and overall annual property taxes. Using the 2009-13 ACS five-year estimates and 2014-18 ACS five-year estimates, the average effective property tax rate is calculated by dividing the total aggregate property taxes paid by all homeowners in a county by the total aggregate home values in that county. Since the five-year ACS estimates must be based on several years of data, I can estimate the average effective property tax rates for over 3000 counties.

Table 14: Descriptive Statistics of Property Tax Rates in the Sample

Year	Count	Mean	Sd	Min	Max
2013	3,132	0.96	0.46	0.03	2.86
2018	3,132	0.96	0.47	0.01	3.11

Figure 8: Effective Property Tax Rates in 2013

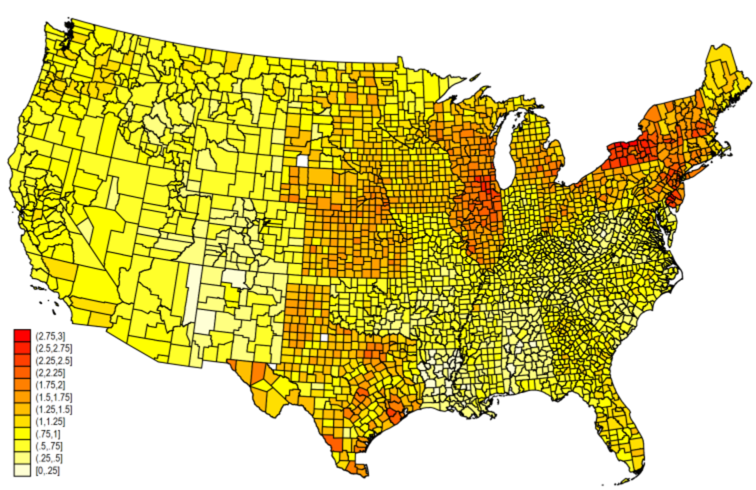
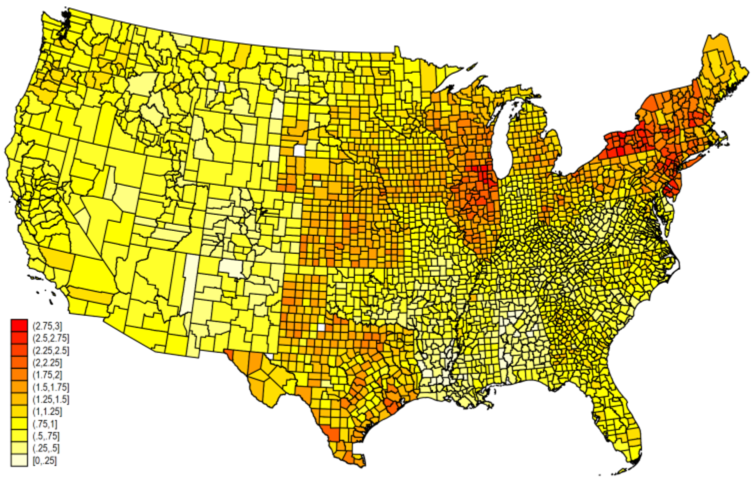


Figure 9: Effective Property Tax Rates in 2018



Appendix A.2

The county-level median home value in dollars

The Housing Price Index (HPI) is one common way to capture the housing market condition. For example, Table 15 shows the HPI for Suffolk county, New York and Orange county, California from 2000 to 2019. Because the HPI is computed based on a base year in a specific area, I cannot directly compare the housing prices across counties. It is possible to compare the percentage change in housing prices across counties, but that does not provide enough information. Therefore, instead of the HPI, I use the estimated median home value in dollars in county j to capture the county-level housing market condition. I estimate it over time using two data sources, the HPI from the Federal Housing Finance Agency (FHFA) and median home value in dollars from the American Community Survey (ACS). From the base year, I compute the median home values in dollars over time with the percentage change in HPI. This is the same methodology the National Association of Realtors (NAR) uses. (NAR, 2017)

Table 15: HPI Example: Suffolk, NY and Orange, CA

County	Year						
	2000	2001	2002	···	2017	2018	2019
Suffolk, NY	100	111.95	127.27	···	174.70	185.70	193.86
Orange, CA	100	110.35	124.85	···	233.55	245.75	251.61

Table 16: Descriptive Statistics of Median Home Value in Dollars ($ thousands) in the Sample

Year	Count	Mean	Sd	Min	Max
2011	2418	143.27	86.54	46.71	856.37
2012	2418	141.86	85.93	45.96	892.12
2013	2418	144.97	91.15	47.14	911.46
2014	2417	150.81	101.27	49.71	1037.05
2015	2415	156.42	106.86	46.39	1097.42
2016	2418	162.95	114.72	49.93	1206.82
2017	2418	171.08	124.66	51.75	1351.73
2018	2416	179.79	131.21	52.32	1393.94

Appendix B

To know the homeowner's tax schedule, I need to compute the estimated amounts of the itemized deduction and then compare it with the amounts of the standard deduction. The amount of the itemized deduction is the sum of state and local taxes, charitable giving, and mortgage interest the homeowner paid in a year. To calculate the amount of the itemized deduction, I need to know state and local income taxes SIT_{ij}, amounts of charitable giving CH_{ij}, and amounts of mortgage interest paid at the w_{ij}^{th} year from the house purchase $MI_{ij}^{w_{ij}}$ of the homeowner i. The amount of the standard deduction is determined by the tax code.

Appendix B.1

State and local taxes

Denote SALT_{ij} as the state and local tax, which is the sum of state and local income taxes and property taxes. Instead of calculating the state income tax of all the individuals, I use the individual income tax return (Form 1040) statistics from the Internal Revenue Service. With the household income information of each seller, I match the average of the state and local income taxes by the size of income and by the state with the sample in the NAR survey. For property taxes, I assume the level of assessment is 100 percent of the market value so that the sales price P^s_{ij} becomes the tax assessment, which is common in most states. With each county's estimated effective property tax rates, I can compute the expected property taxes for the homeowners, which is $\tau^p_j P^s_{ij}$.

Amounts of charitable giving

Due to data limitations, I cannot determine the exact amounts of charitable giving the homeowner did. Similarly to how I obtain information on state and local taxes, I match the average amounts of charitable giving by the size of income and by the state with the sample in the NAR survey.

Mortgage interest paid

To compute the amounts of the mortgage interest deduction at the w^{th}_{ij} year from the house purchase $MI^{w_{ij}}_{ij}$, I need to calculate the amounts of each year's mortgage interest first. I obtain it by calculating the cumulative interest paid at the end of any period year.". After having it, I can apply the mortgage interest deduction rule in Appendix B.2. The notation I use below is or irrelevant to model in the body text.

The monthly payment for the fixed-rate mortgage

Let the total loan term be N and monthly mortgage payment be c. Let r be interest rate per month.

- Amount owed at month 0: P_0
- Amount owed at month 1: $P_1 = [P_0 (1+r)] - c$
- Amount owed at month 2: $P_2 = P_1 (1+r) - c = \left[P_0 (1+r)^2\right] - [c \{1 + (1+r)\}]$
- Amount owed at month 3: $P_3 = P_2 (1+r) - c = \left[P_0 (1+r)^3\right] - \left[c + (1+r) c + (1+r)^2 c\right]$

$$\vdots$$

- Amount owed at month N: $P_N = \left[P_0 (1+r)^N\right] - \left[c\left\{1 + (1+r) + \cdots + (1+r)^{N-1}\right\}\right]$
- P_N will be wzero in the end because the mortgage has been paid off. Thus, I can solve for c using $P_N = 0$. The monthly mortgage payment amount c is

$$c = P_0 \left\{\frac{r(1+r)^N}{(1+r)^N - 1}\right\} = P_0 \left\{\frac{r}{1-(1+r)^{-N}}\right\}.$$

The cumulative interest paid at the end of any period G

First, calculate the amount of interest paid I.

- Amount of interest paid at month 1: $I_1 = P_0 r$
- Amount of interest paid at month 2: $I_2 = P_1 r = [P_0 (1+r) - c] \times r$
- Amount of interest paid at month 3: $I_3 = P_2 r = \left[P_0 (1+r)^2 - [\{c + (1+r) c\}]\right] \times r$

$$\vdots$$

Second, derive the amount of interest paid at month k.

- Amount of interest paid at month k:

$$I_k = P_{k-1} r = \left[\left\{P_0 (1+r)^{k-1}\right\} - c\left\{1 + (1+r) + \cdots + (1+r)^{k-2}\right\}\right] \times r.$$

- After simplifying R_k,

$$\begin{aligned} I_k &= \left[\left\{P_0 (1+r)^{k-1}\right\} - c\left\{1 + (1+r) + \cdots + (1+r)^{k-2}\right\}\right] \times r \\ &= \left\{r P_0 (1+r)^{k-1}\right\} - c\left\{(1+r)^{k-1} - 1\right\} \\ \therefore I_k &= (1+r)^{k-1}(r P_0 - c) + c. \end{aligned}$$

Last, I can determine the cumulative interest paid at the end of any period G, $S(G)$. I add each month's I_k from 1 to G,

$$
\begin{aligned}
S(G) =& \sum_{k=1}^{G} I_k \\
&= (rP_0 - c) \sum_{k=1}^{G} (1+r)^{k-1} + c \times G \\
&= (rP_0 - c) \left(\frac{(1+r)^G - 1}{r} \right) + c \times G.
\end{aligned}
$$

The approximation of the estimated mortgage interest per year through the $S(G)$

Let the estimated mortgage interest per year at the w_{ij}^{th} year from the house purchase be $EI_{ij}^{w_{ij}}$. Let numeric purchase month be M and numeric owning years be y. I approximate the $EI_{ij}^{w_{ij}}$ through the $S(G)$. At purchased year, y will be zero and $S(12-M)$ provides the mortgage interest in that year. After the purchased year $y > 0$, the mortgage interest paid in that year will be $[S(12y + (12-M))] - [S(12(y-1) + (12-M))]$. For example, when the buyer purchased the house in April 2018, $M = 4$, and the owning year $y = 0$ in 2018. In 2018, the buyer paid mortgage interest eight times, and thus $EI_{ij}^{0} = S(8)$. In 2019, he owned his house for one year and thus $y = 1$. Through 2019, the buyer paid mortgage interest 20 times, and the cumulative interest paid through 2019 is $S(20)$. To calculate the interest paid only during 2019, I need to subtract the interest paid through 2018, which is $S(8)$ from $S(20)$. Through this process, $EI_{ij}^{1} = S(20) - S(8)$ and $EI_{ij}^{2} = S(32) - S(20)$, and so on. Thus, $EI_{ij}^{0} = S(12-M)$ is

$$
EI_{ij}^{0} = \left\{ (P_0 \times r - c) \left(\frac{(1+r)^{(12-M)} - 1}{r} \right) \right\} + \{ c \times (12-M) \}.
$$

After the purchased year, the $EI_{ij}^{w_{ij}} = S(12y + (12-M)) - S(12(y-1) + (12-M))$ is

$$
EI_{ij}^{w_{ij}} = (12 \times c) + \left(P_0 - \frac{c}{r} \right) \left((1+r)^{12y-M} \right) \left((1+r)^{12} - 1 \right).
$$

Appendix B.2

Tax schedule calculation

Denote $1(TL < q^{TL})$ as an indicator that the potential homeowner's total loan TL for the house is less than a mortgage interest deduction limit q^{TL}. If the total amount of the loan is less than q^{TL}, the buyer can deduct the total amount of interest paid on the mortgage. On the other hand, if the total loan amount is greater than or equal to q^{TL}, the buyer can deduct a partial amount by $\frac{q^{TL}}{TL} \times MI$ as per the tax code.

Before the Tax Cuts and Jobs Act of 2017 (TCJA), the itemized deduction ID_{ij}, standard deduction for single SD_s, and standard deduction for married filing jointly SD_c were

$$\begin{aligned} ID_{ij} &= SALT_{ij} + MI_{ij} + CH_{ij}, \\ SALT_{ij} &= SIT_{ij} + \tau_j^p p_{ij}^s, \\ MI_{ij} &= \left\{1(TL_{ij} < 1000K) \times MI_{ij}\right\} + \left\{1(TL_{ij} \geq 1000K) \times \frac{1000K}{TL_{ij}} \times MI_{ij}\right\}, \\ SD_s &= 6.5K,\ SD_c = 13K \end{aligned} \tag{13}$$

where the amount of the standard deduction is determined by the tax code.

The TCJA changed the tax bracket τ_k and deduction rules for itemized deductions. First, the mortgage interest deduction limit is now \$750,000 of debt. Second, the $SALT$ deduction is subject to a total cap of \$10,000. Last, the standard deduction amount increased almost by double. Denote $1(SALT < 10K)$ as an indicator that the buyer's $SALT$ is less than \$10,000. After the TCJA, they are

$$\begin{aligned} ID_{ij} &= \left[\left\{1\left(SALT_{ij} < 10K\right) \times SALT_{ij}^{AT}\right\} + \left\{1\left(SALT_{ij} \geq 10K\right) \times 10K\right\}\right] \\ &\qquad + MI_{ij}^{w_{ij}} + CH_j, \\ SALT_{ij} &= SIT_j + \tau_j^p p_{ij}^s, \\ MI_{ij} &= \left\{1\left(TL_{ij} < 750K\right) \times MI_{ij}^{w_{ij}}\right\} + \left\{1\left(TL_{ij} > 750K\right) \times \frac{750K}{TL_{ij}} \times MI_{ij}^{w_{ij}}\right\} \\ SD_s &= 12K,\ SD_c = 24K. \end{aligned} \tag{14}$$

Appendix C

Solution of error terms for likelihood contribution

Using $logp^{s}_{ij} = (1-\phi t)\, logp^{l}_{ij} + \varsigma_{ij}$, I compute $\tilde{\varsigma}_{ij}$

$$\tilde{\varsigma}_{ij} = logp^{s}_{ij} - (1-\phi t)\, logp^{l}_{ij}.$$

Then, I draw $\epsilon^{r}_{ij}|\tilde{\varsigma}_{ij}$ and v^{r}. Given $\tilde{\varsigma}_{ij}$, ϵ^{r}_{ij}, and ν^{r}_{j} with the data, the first order condition of Π_{ij} is a function of ζ_{ij}. I solve for ζ_{ij} satisfying this condition,

$$\frac{\partial}{\partial p^{l}_{ij}} \Pi_{ij}\left(\zeta_{ij}\right) = 0.$$

Thus, I have a set of $\left\{\tilde{\varsigma}_{ij}, \epsilon^{r}_{ij}, \tilde{\zeta}_{ij}\right\}$ using the data and model.

Likelihood contribution represented by corresponding error terms

The likelihood contribution of the choice variables in equation (10) can be computed by transforming the corresponding error terms using the Jacobian-transformation. It can be represented as

$$\begin{aligned}\mathcal{L}_{ij}\left(\theta|\varsigma_{ij}, u_{ij}, \nu_{j}\right) = & \left\{ f_{\varsigma}\left(\tilde{\varsigma}_{ij}\right) \cdot f_{\zeta}\left(\tilde{\zeta}_{ij}|\tilde{u}_{ij}, \tilde{\varsigma}_{ij}\right) \cdot \left| \frac{\partial\left(\tilde{\varsigma}_{ij}, \tilde{\zeta}_{ij}\right)}{\partial\left(logp^{s}_{ij}, logp^{l}_{ij}\right)} \right| \times f_{u}\left(\tilde{u}_{ij}\right) \cdot \left| \frac{\partial \tilde{u}_{ij}}{\partial t} \right| \right\}^{(1-b_{i})} \\ & \times \left\{ f_{\varsigma}\left(\tilde{\varsigma}_{ij}\right) \cdot f_{\zeta}\left(\tilde{\zeta}_{ij}|\tilde{u}_{ij}, \tilde{\varsigma}_{ij}\right) \cdot \left| \frac{\partial\left(\tilde{\varsigma}_{ij}, \tilde{\zeta}_{ij}\right)}{\partial\left(logp^{s}_{ij}, logp^{l}_{ij}\right)} \right| \times S_{ij}\left(t = 99|p^{l}, \epsilon\right) \right\}^{b_{i}} \end{aligned} \tag{15}$$

where u_{ij} is an underlying standard uniform error that does not explicitly appear in the survival function, and thus $f_{u}\left(\tilde{u}_{ij}\right) = 1$.

Jacobian transformation

Jacobian transformation for the listing price and sale price is

$$\left|\frac{\partial\left(\xi_{ij},\tilde{\zeta}_{ij}\right)}{\partial\left(logp^s_{ij},logp^l_{ij}\right)}\right|=\left|\begin{pmatrix}\frac{\partial\xi_{ij}}{\partial logp^s_{ij}} & \frac{\partial\xi_{ij}}{\partial logp^l_{ij}}\\ \frac{\partial\tilde{\zeta}_{ij}}{\partial logp^s_{ij}} & \frac{\partial\tilde{\zeta}_{ij}}{\partial logp^l_{ij}}\end{pmatrix}\right|=\left|\begin{pmatrix}J_{11} & J_{12}\\ J_{21} & J_{22}\end{pmatrix}\right|.$$

From $logp^s_{ij}=(1-\phi t)\,logp^l_{ij}+\varsigma_{ij}$,

$$J_{11}=\frac{\partial\xi_{ij}}{\partial logp^s_{ij}}=1.$$

Because error term ξ_{ij} related to finalizing the sales price does not affect the listing price,

$$J_{12}=0.$$

Given $\tilde{\epsilon}^r_{ij}$, because the error term $\tilde{\zeta}_{ij}$ in the cost function affects the listing price but does not influence the sales price,

$$J_{21}=0.$$

To compute J_{22}, I take the total derivative with respect to $logp^l_{ij}$ and ζ_{ij} on $\frac{\partial}{\partial p^l_{ij}}\Pi'_{ij}\left(\zeta_{ij}\right)$.

Jacobian transformation for the time on the market is

$$\left|\frac{\partial\left(\tilde{u}_{ij}\right)}{\partial\left(t\right)}\right|=\left|S_{ij}\left(t|logp^l,\epsilon\right)\lambda_{ij}\left(t|logp^l,\epsilon\right)\right|.$$