# Gender, Stress, and Job Performance:
# Agents in the Resale Housing Market

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*Abstract.* Existing empirical evidence reveals gender differences in decision making, negotiation, and other behavior. This paper addresses a largely neglected dimension, differences in male and female job performance during periods of personal life stress. The analysis reveals that gender differences not only exist: they vary by type of stress. We use resale housing market transactions data to examine changes in male and female agent sales performance when filing personal bankruptcy and when charged with legal infractions, two different stress events. Bankruptcy is not an unexpected event while interactions with the legal system indicated in crime reports are more likely unanticipated. We take into account both choice of properties to list and how agents serve the clients they represent. Our empirical approach also provides evidence on the extent to which these personal life events identify types of agents who normally conduct business differently versus temporary changes in professional behavior during periods of stress. The results indicate that both bankruptcy and legal infractions signal types of agents with particular business practices as well as changes in their behavior during temporary periods of stress. Further, the differences in male and female responses differ across these events.

## INTRODUCTION

There is considerable evidence of gender differences in decision making, negotiation, and other behavior that can affect job performance. There also appear to be gender differences in responses to stress, although the limited existing evidence tends to focuses on individual behaviors outside the work environment. This paper begins to fill this gap, offering evidence of differences in male and female job performance during periods of personal life stress associated with bankruptcy or being charged with legal infractions.

We study the effects of stressful periods on real estate agents working in the resale housing market, a setting that allows us to infer individual agent productivity from transaction outcomes. The mix of agents in the market allows us to extend the usual male-female comparison to examine how the gender performance differential found earlier in the literature changes for agents experiencing stressful events. The analysis takes into account the possibility that the events themselves may indicate different types of agents who normally conduct business differently. It also recognizes possible sample selection effects arising from agents choosing different types of property to represent while they are under stress.

The estimates reveal that gender differences in response to stress exist, but they are not the same for the two types of stress events examined here. Bikmetova et al. (2023) argue that bankruptcy and other stress events may both identify a type of agent as well as a period of stress from the event itself and develop a novel empirical approach to identify differences in agent behavior associated with agent type from their responses to the event itself. This paper extends the approach, focusing on possible differences in male and female agent performance associated with agent types and responses to events. Starting with personal bankruptcy, to control for the possibility that individuals who go through bankruptcy may be individuals who normally do business differently when compared with those who do not go through bankruptcy, we first identify agents who have or will file for bankruptcy sometime in their lives. Next, we combine full sample and repeat listings analysis to sort out possible sample selection effects. Our findings suggest that compared to male agents who go through bankruptcy at some point, the same type of female agent does not appear to focus on different properties to list, but tends to set lower listing prices for their listings. The evidence drawn from the multi-equation model of selling price and liquidity outcomes also shows systematic differences between transactions completed by male and female agents. Female agents who experience bankruptcy at some point tend to sell their listings quicker but for lower prices than their male counterparts. The difference in performance does not appear to be driven by gender-specific sample selection. Looking at selling agents, those bringing buyers to transactions, we find that female selling agents who file for bankruptcy at some point are associated with quicker salesWe find that female listing agents take longer to sell, while selling agents are engaged in quicker sales for transactions that occur around the bankruptcy filing itself.

We also examine citations or arrests for legal infractions as an indicator of a different type of stress in an agent's personal life. Bankruptcy and legal infractions differ in many respects, including the fact that bankruptcy filing is the end result of a lengthy process and so is not an unexpected event. In contrast, legal infractions indicated in crime reports are more likely unanticipated. The types of stress differ and, perhaps not surprisingly, so do the effects on male vs. female job performance. Following the approach used in the bankruptcy analysis, the estimates clearly show that female agents who have citations or arrests at some time in their lives choose different houses to list and set lower listing prices than male agents who have citations or arrests at some time in their lives. The sales strategy of females appears to change from their personal baseline during the event period itself. The analysis of transactions outcomes also shows no difference between male and female crime report effects on price or liquidity outcomes, both for transactions engaging agents who ever have such legal issues and for those occurring when the issues occur.

These results are new and add to the broader literature identifying differences in male and female job performance. In this regard, clearly, stress is not stress; the nature of the event associated with stress matters. Male and female agents respond differently in terms of prices and liquidity to different types of stress, bankruptcy and legal infractions in this study. Nonetheless, while the nature of the stress events identified here differs, the results indicate that both bankruptcy and legal infractions signal types of agents with particular business practices to a greater extent than changes in their behavior during temporary periods of stress. Further, the extent to which business practices or behavior changes differ across genders varies by the type of event creating stress.

## BACKGROUND LITERATURE

There is considerable literature studying the extent to which males and females behave differently in similar settings. While results are mixed, there is substantial evidence of gender differences in work related settings. Dawson (1997) shows that there are significant ethical differences between salesmen and saleswomen in relational situations. Onemu (2014) finds different male and female worker responses to individual and group incentives schemes. Bajtelsmit and VanDerhei (1997), Hinz et al. (1997), Sunden and Surette (1998), and Barber and Odean (2001) identify gender differences in investment strategy and performance. The literature reviews of Mazei et al. (2015), Kugler et al. (2018), and Hernandez-Arenaz and Iriberri (2019) identify gender differences in both willingness and ability to negotiate and that these are sensitive to the characteristics of the negotiation. There is evidence women tend to negotiate worse outcomes than men (Croson and Gneezy 2009, Castillo et al. 2013, Dittrich et al. 2014, Leibbrandt and List 2014, Card et al. 2016, Blau et al. 2017, Goldsmith-Pinkham and Shue 2020, Roussille 2020, Biasis and Sarsons 2022) and that the mix of genders on each side of negotiations can affect outcomes (Holm 2000, Gneezy, et al. 2003, Sutter, et al. 2009, Pham et al. 2022).

On the other hand, some research finds no significant differences between females and males after controlling for abilities, knowledge, and selection bias in a variety of settings (Master and Meier 1988, Johnson and Powell 1994, Atkinson, Baird and Frye 2003, Seagraves and Gallimore 2013, Andersen et al. 2020).

Looking at real estate brokerage in particular, while many studies find performance differences in female and male real estate agents, some do not. Examples of the range of results include: Turnbull and Dombrow (2007) find no significant agent sex effect on house selling prices; Salter et al. (2012) find female agents obtain higher prices; and Seagraves and Gallimore (2013) conclude that the higher price and shorter time on market for female agents are because of the properties to represent rather than how they service those properties. Bian et al. (2023) find significantly different female and male agent changes in behavior during the covid pandemic.

There also is a substantial literature dealing with how job performance in general is affected by personal life events, ranging from vacation trips (Yermack 2014), marriage and divorce (Wheatley et al. 1991, Lu, Ray, and Teo 2016, Neyland 2020), family deaths or hospitalization (Bennedsen, Pérez-González, and Wolfenzon 2010, 2012, Shu, Sulaeman, and Yeung 2017) to financial reverses (Pool et al. 2019, Maturana et al. 2020, Bikmetova et al. 2023). More generally, Haushofer et al. (2021) suggest that stress may increase the propensity to choose sooner outcomes, irrespective of whether this leads to a smaller monetary gain, loss, or effort.

But what do we know about differences in female and male work responses to non-work related stress events? While the preceding summary identifies a large body of empirical evidence regarding gender differences in general and another regarding the effects of external stress on work performance, few studies focus on gender differences in work productivity arising from stress events. Cahlikova et al. (2020) provide general results, measuring male and female competitive performance in an experiment where individuals are exposed to psychological stress in the form of a psychosocial stressor (that is, a stressor involving social interaction, evaluation, or a threat to social status). They find gender-specific effects. Agarwal et al. (2018) focus on risk aversion to explain gender work performance differences.[1] What is missing is an empirical analysis of the relationship between gender and job performance during periods of stress in one's personal life, drawn directly from non-experimental settings. This is what this study offers.

## DATA

The house transaction data comes from multiple listing service (MLS) records for Gwinnett County in Georgia over 2004-2019. The sample period ends before the onset of the Covid-19 pandemic and its unique effects on the housing and brokerage markets (Bian et al. 2022). It provides listed, sold, expired, and withdrawn houses with various property and location characteristics, listing and selling prices, and identifies the agents involved in each transaction. We keep only properties for resale that are at least two years old to avoid pricing effects that are unique to new construction (Munneke et al. 2015, 2019). We only keep transactions of single-family detached and single-family townhouses and townhome condominiums in the sample. We measure liquidity as time on the market (*TOM*), the difference between the reported off-market date and

[1] See Byrnes et al. (1999) for a summary of the earlier literatue on these questions.

the listing date plus one. We also exclude transactions reporting obvious errors and outliers in the upper or lower 1% of the distributions of the observed sale price or time on the market.

We obtain agent information from several sources. We only include transactions involving full-time listing or selling agents, where full-time is defined as being involved in at least 3.5 transactions per year on average. Agents not meeting this criterion are considered part-time and are indicated as such in their transactions with full-time agents. We exclude transactions with companies buying and selling real estate through technology (e.g., *iBuyer*) or assisted by discount brokers[2] because the different business models may have as yet undetermined effects on prices and liquidity (Buchak et al. 2020a, 2020b). We supplement the MLS data with active and non-active agent license records from the Georgia Real Estate Commission (GREC). GREC provides full names and addresses, which we use to identify agent residence locations.[3] In addition, each full-time agent's age and full name or address used to identify agents in public records background reports from the BeenVerified.com website. For each full-time agent, we perform a manual background search via the BeenVerified.com website. BeenVerified provides a directory with access to an individual's date of birth, address, phone, employment histories, criminal and court records, property records, and other public records, which can be searched by name within a specific city, county, and state as well as nationwide.

To test for differences in the financial distress associated with bankruptcy and other types of personal stress, we focus on two types of events reported in public records – bankruptcy filings

[2] We exclude such iBuyers as Knock, Opendoor, Offerpad and others that do not rely on traditional agency relationships. We also sort all agents in descending order by the average number of completed transactions per year separately on listing or selling sides and manually check those near the top of the list to identify other firms engaging in similar operations.

[3] The agent address information reported by GREC is supplemented with the active address from BeenVerified. Individuals with similar names are checked by hand using middle names and listed profession to identify which is the agent in our sample. Agent names that cannot be identified with these methods are excluded from the sample of agents.

and arrests or citations. For bankruptcy, we collect and aggregate each full-time agent's public bankruptcy filing records, not limited by their current state of residence or specific years. Each record contains the case number, filing and discharge dates, bankruptcy chapter, and filing type. We focus on the filing date. Significant financial distress, such as bankruptcy, may have separate short-run and long-run implications. Therefore, we construct several indicators for a listing or selling agent experiencing bankruptcy any time before or after the house transaction, *LA_ever_bankrupt* and *SA_ever_bankrupt*, respectively, as well as filing for bankruptcy within six months of the transaction, *LA_bankruptcy_event* and *SA_bankruptcy_event.* [4]

In addition, we draw from public criminal records for each full-time agent to assemble alternative personal stress event variables. These records typically contain the case number, offense date and details, court date, and other relevant details. Most records for our sample of agents are associated with motor vehicle violations like license or traffic violations including hit and run, speeding, or driving under impairment. Trespassing, theft, resisting arrest and other misdemeanors are less common. Following the approach used for the bankruptcy variables, we construct indicators for agents with offenses, citations, or arrests occurring at any point of their life (*LA_ever_crime*, *SA_ever_crime*) or within six months of the house transaction (*LA_crime_event*, *SA_crime_event*).

We use an agent's first name to determine gender with the Python gender-guesser package[5]. The software uses the dictionary file containing a list of more than 40,000 first names and gender and covers the majority of first names in all European countries and the US as well. We focus on the first name as reported in GREC and provided by BeenVerified. We then manually

[4] The empirical results reported here identify the bankruptcy or crime record event as 6 months before and 6 months after property listing. We also test longer before windows of 12, 18, and 24 months and find that our conclusions are not sensitive to the window length.
[5] Available at https://pypi.org/project/gender-guesser/

check unclassified names by searching agents online. To validate our classification, we count the frequency of each male and female name in the agents' sample. Figures 1 and 2 present word clouds with the most frequent agent male and female names. These suggest that our classification accurately captures the gender of most of the agents and this key variable is constructed correctly.

The resultant data set contains information about agent characteristics, including the number of completed transactions, their residence location, gender, and financial and personal distress measures. Our central variables of interest are gender and stress indicator interaction terms.

Buyer and seller data comes from the Georgia Property Tax Assessor database merged with the MLS data using property spatial coordinates and transaction date. We select the name of the first party reported as involved in each side of the transaction to determine whether a financial institution or a company is involved in the transaction as a direct buyer or seller.

We also control for several socio-economic neighborhood conditions in the models. We obtain census tract annual data related to age, education, and median household income from 2010-2020 American Community Surveys.[6] We use the consumer price index (CPI) from the Bureau of Labor Statistics to express all monetary values in 2010 dollars. ZIP code fixed effects in all models control unobserved neighborhood characteristics. All models also include listing or selling year-quarter fixed effects.

The resulting data cover 2004 through 2019. The ending date avoids dealing with idiosyncratic pandemic effects in the housing market. Merging the MLS and property data yields 129,124 listings, 97,597 completed transactions, 39,621 repeat listings and 13,354 repeat sales. Table 1 defines the key agent-related variables that are the focus of this study. All other variables

[6] As 2010 is the earliest year for our American Community Survey data, we use 2010 neighborhood controls for observations in 2004-2010.

pertaining to property and neighborhood characteristics and investor buyers and sellers used in the analysis are defined in the appendix reporting complete model estimates.

Table 2 reports the mean selling prices for agents with and without stress exposure by gender. Transaction prices for listing and selling agents around the time they file for bankruptcy are significantly lower than for agents who have not filed for bankruptcy, which by itself suggests poorer sales performance. The price levels and differences with and without stress are not the same for female and male agents. The price differences for agents who ever file for bankruptcy when compared with those who have not also differ by gender, although in this case the mean price for males who ever file for bankruptcy is not significantly different from that for males who never file for bankruptcy. The transaction price pattern for stress associated with legal infractions is similar to bankruptcy stress in that most agents (except selling agents of either gender who ever experience the stress event) have significantly different prices than agents without the stress exposure and the differences vary by gender. These comparisons, of course, do not control for property characteristics or other factors affecting prices. Still, the patterns suggest that agent stress exposure may affect transaction outcomes. While prices in transactions involving agents under stress tend to be lower, these effects differ by gender as well as the nature of the stress itself.

## BANKRUPTCY STRESS EFFECTS

Looking first at how bankruptcy stress affects agent performance, table 4 reports probit model marginal effects of listing agent characteristics on the probability that listed properties sell within the window indicated for each column. Columns (1)-(4) provide key agent-related marginal effects when controlling for the bankruptcy filing event and columns (5)-(8) when including the ever bankrupt variables as well. The broad implications of the two models are the same, except as noted in what follows.

Part-time agents, those involved in fewer than 3.5 transactions per year, exhibit greater marginal probabilities of sale the longer the window, indicating lower liquidity for both specifications. Agent experience measures the number of transactions previously completed (Gilbukh and Goldsmih-Pinkham (2023). The negative but diminishing (in absolute value) marginal effects of agent transaction volume (*LA_experience*) also imply slower sales for higher volume agents, consistent with per client effort thinning by high volume agents found by Bian et al. (2015). Houses listed in the agent's home neighborhood (*LA_neighborhood*) are more likely to take longer to sell. Agents who co-list properties with other agents (*LA_coagent*) show no consistent significant marginal sale probability pattern across the windows.

Turning to the main variables of interest, female listing agents (*LA_female*) exhibit a greater probability of selling properties within three months. Columns (1) and (3) indicate lower probabilities of faster sales by male agents filing bankruptcy (*LA_banktuptcy_event*), but columns (5)-(8) show that this effect is actually an artifact of the lower liquidity associated with male agents who ever file bankruptcy (*LA_ever_bankrupt*). The conclusions are different for female agents as indicated by the interaction variables *LA_banktuptcy_event*LA_female* and *LA_ever_bankrupt *LA_female*. The estimated marginal effects show different bankruptcy effects on liquidity for men and women agents. Female agents who ever file for bankruptcy exhibit somewhat weaker negative marginal effects on the sales probabilities in each window when compared with male agents who file for bankruptcy sometime. Whereas the bankruptcy event itself does not affect liquidity for male agents, the significantly negative on the female interaction variable indicate significantly slower sales when compared with males.

Listing agents advise their property sellers when setting the listing price (*LP*), so the listing price reflects, at least to some extent, the listing agent's selling strategy (Anderson, et al. 2014). The listing price for property *i* listed at *t* is a function of the vector of property and neighborhood characteristics (including location fixed effects), $X_i$, the vector of agent characteristics, $A_{it}$, time fixed effects, $T_{it}$ , and the stochastic term.

$$lnLP_{it} = \alpha X_i + \sigma A_{it} + \delta_t T_{it} + u_{it} \qquad (1)$$

Table 5 reports key parameter estimates for listing price models with and without the bankruptcy variables. The non-stress variable coefficient estimates are robust across the models. Properties listed with part-time agents and higher volume agents tend to have lower listing prices while properties in the agent's neighborhood tend to have higher listing prices. Female agents set higher listing prices.

When evaluating bankruptcy effects, the ever bankruptcy variables capture any systematic listing price effect associated with the type of agent who experiences bankruptcy sometime in their life, but not during the current transaction. When included in models with the bankruptcy event variables, the coefficients on the event variables pick up any systematic difference in listing price strategy during the event relative to other times for this type of agent. The sum of the ever bankrupt and bankruptcy event coefficients indicate any pricing differences of agents currently going through bankruptcy relative to agents who never go through bankruptcy.

The bankruptcy event coefficient estimate reported in table 5 indicates that the stress event does not influence either male and female agents' listing strategies. Nonetheless, the ever bankrupt coefficient estimates suggest that the type of female agent who files for bankruptcy sometime in their life pursues a different listing strategy from those who do not file bankruptcy. Female agents who ever file for bankruptcy set significantly lower listing prices than male agents who ever file (as indicated by the *LA_ever_bankrupt* * *LA_female* coefficient) or other female agents (as indicated by the sum of the *LA_ever_bankrupt* and *LA_ever_bankrupt* * *LA_female* coefficients). The listing price strategies of female and male agents clearly differ in this regard.

While the preceding takes into account the type of agent and the event, it does not allow for the possibility that bankruptcy may simply indicate a type of agent who conducts business differently, and who therefore may choose to list different types of houses. One way to remove this possible selection bias in the estimates is to examine repeat listings, examining the same house listed with different agents at different points in time, $t$ and $t + s$, which yields the following estimating equation from (1)

$$lnLP_{it+s}/LP_{it} = \delta_{t+s} T_{it+s} - \delta_t T_{it} + \sigma(\mathrm{A}_{it+s} - \mathrm{A}_{it}) + u_{it+s} - u_{it} \qquad (2)$$

The right hand side first terms capture the two periods the repeated listings occur, and in that way resemble the standard single-equation repeat sales price model. The additional vector differences $\Delta\mathrm{A} = \mathrm{A}_{it+s} - \mathrm{A}_{it}$ capture the focus of our interest in this study, agent effects on listing. Table 6 reports the key agents and bankruptcy variables coefficient estimates. A direct comparison of full sample and repeat sample estimates provides insight into the selection bias in the full sample estimates.

The female coefficient is significantly larger in the repeat listings model than the full sample model, indicating that female agents tend to work with lower price listings than their male counterparts. The ever bankrupt coefficient is positive and significant in the last model in table 6, evidence that bankruptcy indicates a type of male agent, and this type of male agent sets higher listing prices. The significant event coefficient shows that while this type of agent chooses to work with certain properties, the agent also alters their listing strategy during the stress event itself. The ever bankrupt and the interaction term coefficients together, however, indicate that this type of female agent tends to set lower listing prices than both this type of male agent and agents who do not experience bankruptcy. And unlike their male counterparts, this type of female agent does not appear to change her listing strategy for the properties she works with during stress periods.

Having established the gender differences in listing strategies, we now consider the effects of agent bankruptcy on another dimension of job performance, transactions outcomes. The resale housing market is a search market in which transaction price and liquidity or time on the market of each property are simultaneously determined (Krainer 2001). These observable transactions outcomes reflect the interplay of the distributions of heterogenous buyers, sellers and properties listed for sale during the same time frame mediated by agents' search, matching and sales efforts. One consequence of empirically modeling search market equilibria is that price and liquidity both are determined by the same set of factors. Applying the generalized search framework of Turnbull and Zahirovic-Herbert (2012), the reduced form equilibrium transaction outcome for property $i$ sold at time $t$ is the selling price (*SP*) and time on the market (*TOM*) described by the set of equations

$$lnSP_{it} = \alpha X_i + \sigma A_{it} + \delta_t T_{it} + u_{it} \tag{3}$$

$$lnTOM_{it} = a\, X_i + sA_{it} + d_t T_{it} + v_{it} \tag{4}$$

where X and A are vectors of the property and agent (both listing and selling agents) characteristics, $T_{it}$ are time period (quarter) fixed effects and $u$ and $v$ are stochastic errors. Because *SP* and *TOM* are simultaneously determined in equilibrium, the error terms may be correlated across equations, which calls for seemingly unrelated regression (SUR) to obtain asymptotically efficient coefficient error estimates.

Table 6 reports key parameter estimates for equations (3)-(4). We begin by noting that agent characteristics coefficient estimates unrelated to bankruptcy are robust across the 3 models. Part-time listing agents take longer to sell the houses they represent while part-time selling agents, those bringing buyers to the transaction, have higher selling prices. Houses in the listing agent's neighborhood tend to sell for more and those in the selling agent's neighborhood sell more quickly. Higher volume listing and selling agents each tend to obtain lower prices but engage in quicker sales. *LA_Dual_agent* identifies individual listing agents who also bring the buyer to the transaction. These situations yield lower prices and less liquidity. The coagent variable indicates that houses listed with partner agents working together sell for more and more quickly than those listed by one agent. The superior coagent performance is likely the result of individual agents exploiting their comparative advantages in the mix of tasks essential to finding a buyer and successfully closing the sale.

Turning to the variables of central interest, the ever bankrupt estimates for both male listing and selling agents yield no price effect but a longer time to sell the property. Ever bankrupt selling agents are also associated with lower prices. The bankruptcy event has no effect on either dimension of transactions. On the other hand, female listing agents who are ever bankrupt sell faster and obtain lower prices. Once again it appears that agents who ever experience bankruptcy differ from those that do not and the female bankruptcy type differs from the male bankruptcy type as reflected by the difference in job performance. The listing agent event variables reveal that this type of male agent does not change behavior during the event while this type of female agent takes longer to sell their listing.

On the selling agent side, the type of male agent who experiences bankruptcy tends to transact with houses that are on the market longer, at lower prices. The results, however, are different for female selling agents in that those who ever experience bankruptcy transact with houses that are on the market for a shorter period of time than their male counterparts. Female selling agents filing for bankruptcy do not appear to change their behavior during the stress period.

The estimates in table 6 resemble results from the listing price analysis in that agents who ever file bankruptcy pursue their professional duties differently when compared with agents with no bankruptcy experience. The listing price analysis provides evidence that this type of agent chooses to work with different types of houses, raising the likelihood of selection bias in the price and liquidity estimates reported here. So, following the strategy used in the listing price analysis, we apply a repeat sales approach to remove the possible house selection effect for bankrupt agents, thereby identifying different agent effects when selling the same house repeatedly over time.[7]

To do so, difference the price-liquidity equations (3)-(4) for properties sold at time $t+s$ and $t$ in the sample period to obtain the repeat sales analogue to the reduced form system

$$lnSP_{it+s}/SP_{it} = \delta_{t+s}\, T_{it+s} - \delta_t\, T_{it} + \sigma(\mathrm{A}_{it+s} - \mathrm{A}_{it}) + u_{it+s} - u_{it} \tag{5}$$

$$lnTOM_{it+s}/TOM_{it} = d_{t+s}\, T_{it+s} - d_t\, T_{it} + s(\mathrm{A}_{it+s} - \mathrm{A}_{it}) + v_{it+s} - v_{it} \tag{6}$$

[7] Our repeat sales approach extends the standard repeat sales model to two outcome dimensions—price and liquidity—while it controls selection biases arising from male ever bankrupt type, female ever bankrupt type, male, and female agents' tendency to work with certain types of houses in the market. It is for these reasons that we do not use selection correction methods based on Heckman two stage or propensity score matching techniques to deal with these complicated layered selection effects.

The right hand side first terms in equations (5)-(6) capture the two periods the repeated sales occur, and in that way resemble the standard single-equation repeat sales price model that does not consider liquidity. As before, the vector difference $\Delta A = A_{it+s} - A_{it}$ captures agent effects on price and liquidity. The system is estimated using SUR to control for error term correlation across equations arising from the reduced form nature of the system.

Table 7 reports key parameter estimates for the bankruptcy-related variables alone; full estimates are available in the appendix. Having removed possible selection effects from the estimates, there are important differences when compared with the price-liquidity results reported in table 6. Once again, we find female listing agents and selling agents associated with lower selling prices and faster salesThe type of listing agent who experiences bankruptcy now obtains a higher selling price if male and a lower price if female but males take longer to sell when compared with agents with no bankruptcy experience. The stress event leads to slower sales for females for bankruptcy types.

Looking at the selling agent side, those bringing buyers to the transaction, male agents who ever experience bankruptcy deal with houses that are on the market longer while their female counterparts work with houses that are on the market for a shorter period of time. Neither exhibits significant price effects. Male selling agents deal with houses that are on the market even longer during the bankruptcy filing event period while female selling agents are associated with even quicker sales once the selection effects are removed from the estimates.

LEGAL INFRACTIONS STRESS EFFECTS

We now consider a very different type of stress-inducing event: being charged with a legal infraction. For most people, filing bankruptcy is an event culminating a lengthy period of substantial financial distress. We expect legal infractions involving citations or arrests for traffic violations (mostly hit and run, speeding, or driving under impairment), and trespassing, theft, or other misdemeanors, not to signal the same kind of longer running stressful periods associated with bankruptcy. The question is whether the different nature of stress modifies the differences in agent work performance we observe for female and male agents in the case of bankruptcy.

The transactions outcomes analysis follows that in the previous section. We define two types of event variables for listing and selling agents, if they ever have crime records indicating legal infractions (*LA_ever_crime* and *SA_ever_crime*) or if they have infractions within six months of the house transaction (*LA_crime_event* and *SA_crime_event*). Table 8 reports key variable coefficient estimates for the full sample price-liquidity model and table 9 for the repeat sales models that help remove house type selection effects.

The full sample estimates reveal female listing and selling agent effects on price and liquidity resembling those found earlier. Looking at the stress variables, though, we find that the type of male agent likely to have a legal run-in, as indicated by *LA_ever_crime*, shows no appreciable effect on transaction outcomes. The stress period itself does not affect male agents either. Clearly, this type of agent demonstrates similar job performance when compared with others. The significant female interaction variables indicate that female listing agents ever engaged in legal infractions sell at lower prices.  Same as male listing agents, they do not experience temporary stress when the event happens.  This result differs from the bankruptcy conclusions.

On the selling agent side, the males and females ever engaged in crime sell less liquid houses at higher prices; the price effect for females is weaker. Both males and females change their behavior and lower selling prices during the legal infractions stress period and female selling agents have the same event responses as their male colleagues. These results, too, mostly differ from the bankruptcy conclusions.

The key parameter estimates for the repeat sales models reported in table 9 control for systematic differences in agents' choice of houses to list or sell. We find no significant effects for the type of male or female listing agents who ever have citations or arrests. The event effect for male listing agents on selling price is now positive, providing evidence of a change in job performance during the stress period. Once we control for selection effects, we find differences in sales performance across genders. The female listing agents sell at lower prices than male agents during the stress event period.  Together, the estimates are consistent with legal infractions indicating a different type of agent who conducts their business differently and who also modifies their job performance when the event occurs. In addition, the estimates also show the sexes do not behave the same with respect to how they regularly do business or respond to the event.

Looking at agents who bring buyers to the transactions, the type of male selling agents who are caught for legal infractions increase while females decrease selling prices. The stress event itself, however, has no effects on price or liquidity for both genders.

Drawing all of the results together, legal infractions effects and bankruptcy effects each elicit different changes in job performance for female and male agents. Agents taking the role of listing agents respond differently to stress events when compared with agents taking the role of selling agent. Both bankruptcy and legal infraction records indicate a type of agent who conducts their professional duties differently. This type of agent behavior differs between females and males for bankruptcy (both listing and selling agents) and for legal infractions (selling agents). We cannot, however, determine whether the agent type job performance differences reflect risk aversion, opportunity costs, or skill differences relative to agents who do not experience stress events.

Nonetheless, female and male agents respond differently during the stress event period as well, and the differences are more pronounced in the case of bankruptcy. Comparing the full sample and repeat sales results reveals that the differences in agents' behaviors across genders include choosing different types of houses to work with as well as how they service the clients they chose.

## CONCLUSION

The literature shows females and males exhibit differences in decision making, negotiation, and other work related behavior. There is also limited evidence of gender differences in how individuals respond to stress. This paper provides new evidence on that question, studying gender difference in how stress-inducing events in professionals' personal lives affect their job performance. We study real estate agents in the resale housing market, a setting that provides the opportunity to use observed selling price and liquidity outcomes to infer individual agent job performance. The mix of active agents allows us to compare males and females with and without stress events as well as in different roles as listing and selling agents in transactions. Our approach enables us to evaluate the degree to which the events themselves signal different types of agents who normally conduct business differently or periods of stress that elicit temporary changes in behavior on the job. Our analysis also considers possible sample selection effects from types of agents—male or female, stressed or unstressed—choosing different types of properties to represent.

In general, both bankruptcy and minor legal infractions affect how real estate agents do their jobs, which is consistent with the broader management and finance literature on personal stress and job performance. In addition, though, we find that female and male real estate agents respond differently to these stressful events. For both genders, these events signal certain types of agents who normally conduct business differently, but the way these types of agents behave differs by sex and by their roles as listing or selling agents. In addition, though female and male agents differ in how they respond to bankruptcy stress events or legal infractions. While Agarwal et al. (2018) argue that risk aversion can explain performance differences across genders, we are unable to address this question. We cannot determine the extent to which stress-related differences in job performance are driven by risk attitude, opportunity costs, or different abilities relative to agents who do not experience stress events.

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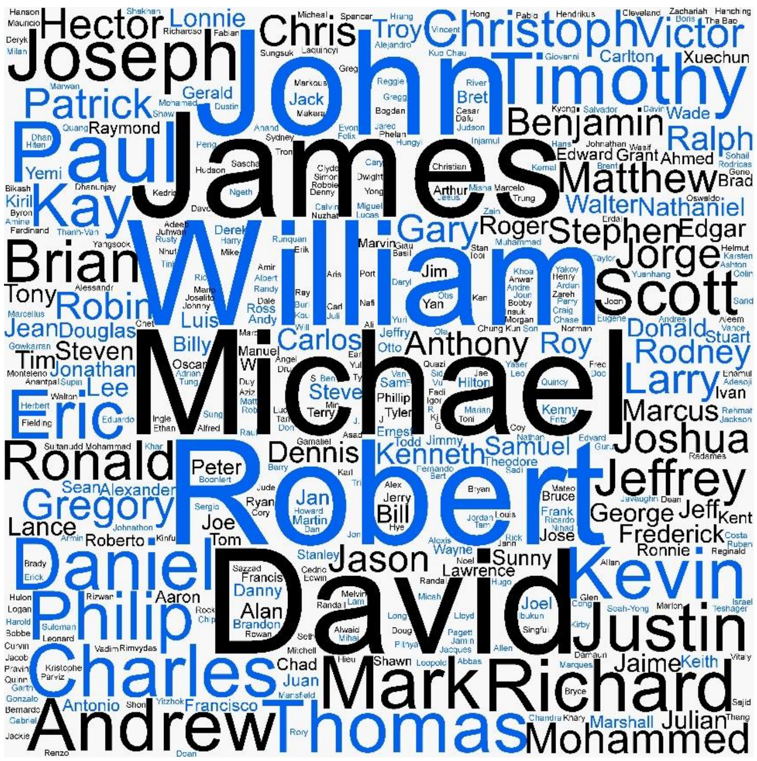


Figure 1 – Name cloud for the most popular sample agent male names


Figure 2 – Name cloud for the most popular sample agent female name

Table 1- Key Agents Variables definition

| Variable | Description and Data Source |
|---|---|
| LA_part_time / SA_part_time | The indicator variable equals 1 for listing (selling) agents selling less than 3.5 on average during years active, or not identified agents. Source: MLS |
| LA_experience / SA_experience | The natural log of one plus the number of completed transactions on *both* the listing and selling sides (regardless of an agent specialization) over the past 12 months. Source: MLS |
| LA_neighborhood / SA_neighborhood | The indicator variable equals 1 for listing (selling) agents residing under the same ZIP-code as property sold. Source: GREC. Public records |
| LA_farming | Agent Farming, accounts for agent specialization through the geographic concentration of agent's inventory. Measured by the ratio list agent's properties in a census tract/and the agent's inventory. |
| LA_market_share | Agent neighborhood market share, measured by the ratio list agent's properties/all properties in the census tract in that year |
| LA_coagent | The indicator variable equals 1 for listing agent has a coagent. Source: MLS |
| Dual_agent | The indicator variable equals 1 for listing agent is a dual agent. Source: MLS |
| LA_Female/SA_Female | The indicator variable equals 1 for listing (selling) agent is a female |
| LA_Male/SA_Male | The indicator variable equals 1 for listing (selling) agent is a male |
| *Stress Events* | |
| LA_ever_bankrupt / SA_ever_bankrupt | The indicator variable equals 1 if a listing (selling) agent ever filed for bankruptcy |
| LA_bankruptcy_event / SA_bankruptcy_event | The indicator variable equals 1 if a listing (selling) agent filed for bankruptcy within 6 months surrounding the transaction |
| LA_ever_crime / SA_ever_crime | The indicator variable equals 1 if a listing(selling) agent ever had criminal record |
| LA_crime_event / SA_crime_event | The indicator variable equals 1 if a listing(selling) agent received criminal record within 6 months surrounding the transaction |

Table 2

Agent Stress Exposure and Selling Prices

This table reports mean selling prices associated with completed transactions over the sample of Gwinnett County MLS sales data over 2004 through 2019. Columns 1 and 2 present the mean for sold properties by listing and selling, males and females agents conditional on stress experience, respectively. Columns 3 and 4 present difference and t-statistic

| | | Selling Price | | | |
|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) |
| | Stress Exposure | No | Yes | Difference | T-stats |
| Female | LA_bankruptcy_event | 203995.76 | 182598.43 | 21397.32 | 3.81 |
| | LA_ever_bankrupt | 206622.34 | 191550.37 | 15071.97 | 12.94 |
| Male | LA_bankruptcy_event | 180677.18 | 170110.40 | 10566.78 | 1.66 |
| | LA_ever_bankrupt | 181108.95 | 178275.10 | 2833.85 | 2.07 |
| Female | SA_bankruptcy_event | 199617.51 | 164330.63 | 35286.88 | 6.97 |
| | SA_ever_bankrupt | 202243.19 | 189088.64 | 13154.55 | 10.44 |
| Male | SA_bankruptcy_event | 181703.61 | 156716.53 | 24987.08 | 4.04 |
| | SA_ever_bankrupt | 184059.07 | 173640.35 | 10418.72 | 7.48 |
| Female | LA_crime_event | 203911.88 | 150827.77 | 53084.11 | 3.80 |
| | LA_ever_crime | 204431.63 | 195502.42 | 8929.20 | 4.85 |
| Male | LA_crime_event | 180569.63 | 211868.48 | -31298.85 | -2.04 |
| | LA_ever_crime | 180713.50 | 179619.59 | 1093.91 | 0.62 |
| Female | SA_crime_event | 199326.76 | 145401.80 | 53924.95 | 4.38 |
| | SA_ever_crime | 199475.22 | 195789.99 | 3685.23 | 1.74 |
| Male | SA_crime_event | 181649.15 | 148603.13 | 33046.02 | 4.10 |
| | SA_ever_crime | 181596.64 | 180514.15 | 1082.49 | 0.59 |

Table 3

Probit Model - Bankruptcy variables estimates

This table reports marginal probabilities calculated for the key variables of interest from probit regressions with sold house indicator as the dependent variable. "Sold" indicator equals 1 is a house is sold within 6, 12, 24 month or ever for models 1-4 and 5-8 respectively, and 0 otherwise. The sample includes all listings from Gwinnett County property records from 2004 to 2020. All models include property, neighborhood, census tract level variables, ZIP code and year-quarter fixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. Corresponding standard errors are in the parenthesis. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | 6 months | 12 months | 24 months | Ever | 6 months | 12 months | 24 months | Ever |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| LA_Part time | 0.2527*** | 0.3942*** | 0.4315*** | 0.4341*** | 0.2436*** | 0.3861*** | 0.4237*** | 0.4263*** |
| | (0.0186) | (0.027) | (0.0303) | (0.0307) | (0.0187) | (0.0271) | (0.0304) | (0.0308) |
| lnLA_Vol | -0.0127*** | -0.0143*** | -0.0147*** | -0.015*** | -0.013*** | -0.0146*** | -0.015*** | -0.0153*** |
| | (0.0041) | (0.0048) | (0.005) | (0.005) | (0.0041) | (0.0048) | (0.005) | (0.005) |
| LA_neighborhood | 0.0168*** | 0.0194*** | 0.0192*** | 0.0192*** | 0.0167*** | 0.0192*** | 0.019*** | 0.019*** |
| | (0.013) | (0.0134) | (0.0134) | (0.0134) | (0.013) | (0.0134) | (0.0134) | (0.0134) |
| LA_farming | -0.1568*** | -0.1338*** | -0.1306*** | -0.1311*** | -0.1531*** | -0.131*** | -0.1281*** | -0.1286*** |
| | (0.0322) | (0.0345) | (0.035) | (0.035) | (0.0322) | (0.0346) | (0.035) | (0.0351) |
| LA_dominance | 0.2285*** | 0.0992 | 0.079 | 0.0774 | 0.1819*** | 0.0602 | 0.0426 | 0.041 |
| | (0.2488) | (0.2688) | (0.2714) | (0.2719) | (0.2491) | (0.2691) | (0.2718) | (0.2723) |
| LA_coagent | 0.0063** | 0.0045 | 0.0036 | 0.0042 | 0.0046 | 0.0027 | 0.0019 | 0.0024 |
| | (0.0109) | (0.0115) | (0.0116) | (0.0117) | (0.0109) | (0.0116) | (0.0117) | (0.0117) |
| LA_FEMALE | 0.0249*** | 0.0226*** | 0.0228*** | 0.0229*** | 0.0209*** | 0.0191*** | 0.0195*** | 0.0195*** |
| | (0.009) | (0.0094) | (0.0094) | (0.0094) | (0.01) | (0.0105) | (0.0105) | (0.0105) |
| LA_ever_bankrupt | | | | | -0.0556*** | -0.0493*** | -0.0472*** | -0.0474*** |
| | | | | | (0.0172) | (0.0182) | (0.0184) | (0.0184) |
| LA_bankruptcy_event | -0.0371* | -0.0321* | -0.0261 | -0.0262 | 0.0075 | 0.0071 | 0.0113 | 0.0113 |
| | (0.0687) | (0.0699) | (0.0702) | (0.0702) | (0.0701) | (0.0714) | (0.0717) | (0.0717) |
| LA_ever_bancrupt*LA_Female | | | | | 0.0197*** | 0.0165*** | 0.0156*** | 0.0159*** |
| | | | | | (0.0221) | (0.0231) | (0.0233) | (0.0233) |
| LA_bancruptcy_event*LA_Female | -0.0345 | -0.0214 | -0.0241 | -0.0242 | -0.0494** | -0.0335 | -0.0354 | -0.0358* |
| | (0.0863) | (0.0866) | (0.0868) | (0.0869) | (0.0881) | (0.0886) | (0.0888) | (0.0889) |
| Property and neighborhood characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP code fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-quarter fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 124771 | 124771 | 124771 | 124771 | 124771 | 124771 | 124771 | 124771 |

Table 4

OLS Listing Price Model - Bankruptcy variables estimates

This table reports coefficient estimates for the key variables of interest from OLS regressions with the natural logarithm of listing price as the dependent variable. The sample includes all transactions from Gwinnett County property records from 2004 through 2029. All models include property, neighborhood and census tract level variables, ZIP code, year-quarter fixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| LA_Part time | 0.0007 | 0.0007 | 0.0007 |
| | (0.3117) | (0.2814) | (0.2812) |
| LA_experience | -0.0075*** | -0.0076*** | -0.0076*** |
| | (-12.6738) | (-12.7115) | (-12.7599) |
| LA_neighborhood | 0.0221*** | 0.0221*** | 0.0219*** |
| | (11.4647) | (11.4491) | (11.3751) |
| lnLA_farming | 0.0404*** | 0.0405*** | 0.0406*** |
| | (8.4048) | (8.4281) | (8.4521) |
| lnLA_market_share | 0.4144*** | 0.4141*** | 0.3958*** |
| | (10.2805) | (10.2759) | (9.8481) |
| LA_coagent | 0.0152*** | 0.0152*** | 0.0146*** |
| | (9.3671) | (9.3712) | (9.0479) |
| LA_Female | 0.0213*** | 0.0214*** | 0.0272*** |
| | (15.6078) | (15.6171) | (17.7652) |
| LA_ever_bankrupt | | | 0.0023 |
| | | | (0.8963) |
| LA_bankruptcy_event | | -0.0152 | -0.0172 |
| | | (-1.3193) | (-1.4699) |
| LA_ever_bancrupt*LA_Female | | | -0.0299*** |
| | | | (-9.2075) |
| LA_bancruptcy_event*LA_Female | | -0.0071 | 0.0174 |
| | | (-0.5079) | (1.2225) |
| Property and neighborhood characteristics | Yes | Yes | Yes |
| ZIP code fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes |
| Adjusted R-Square | 0.7936 | 0.7936 | 0.7939 |
| Number of Observations | 124771 | 124771 | 124771 |

Table 5

OLS Listing Price Model Repeat Listings - Bankruptcy variables estimates

This table reports coefficient estimates for the key variables of interest from OLS regressions with the natural logarithm of listing price as the dependent variable. The sample includes all repeated listings from Gwinnett County property records from 2004 through 2019. All models include competition and agent-level variables and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Intercept | 0.0065 | 0.0063 | 0.0053 |
| | (0.1756) | (0.1692) | (0.1434) |
| d_LA_Part time | -0.0147*** | -0.0148*** | -0.012*** |
| | (-3.4599) | (-3.4832) | (-2.7783) |
| LA_experience | -0.0147*** | -0.0147*** | -0.0147*** |
| | (-14.0645) | (-14.1235) | (-14.1041) |
| d_LA_neighborhood | 0.0181*** | 0.0181*** | 0.0181*** |
| | (5.1293) | (5.1147) | (5.122) |
| d_lnLA_farming | 0.06*** | 0.0601*** | 0.0586*** |
| | (7.2071) | (7.2246) | (7.0501) |
| d_lnLA_market_share | 0.1016 | 0.1015 | 0.0982 |
| | (1.1807) | (1.1796) | (1.14) |
| d_LA_coagent | 0.0029 | 0.0029 | 0.0031 |
| | (1.0586) | (1.0501) | (1.1186) |
| d_LA_Female | 0.0232*** | 0.0233*** | 0.0306*** |
| | (9.6235) | (9.6198) | (11.3162) |
| d_LA_ever_bancrupt | | | 0.0216*** |
| | | | (4.7296) |
| d_LA_bancruptcy_event | | -0.0176 | -0.0332* |
| | | (-1.0033) | (-1.8554) |
| d_LA_ever_bancrupt*LA_Female | | | -0.0372*** |
| | | | (-6.412) |
| d_LA_bancruptcy_event*LA_Female | | 0.0013 | 0.0278 |
| | | (0.0624) | (1.303) |
| Year-quarter fixed effects | Yes | Yes | Yes |
| Adjusted R-Square | 0.4544 | 0.4545 | 0.4551 |
| Number of Observations | 40087 | 40087 | 40087 |

Table 6

Price-Liquidity SUR Model - Bankruptcy variables estimates

TThis table reports coefficient estimates from SUR regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM . All models include property, neighborhood and census tract level variables, ZIP code and year-quarterfixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| LA_Part time | 0.0145*** | 0.0472*** | 0.0144*** | 0.0477*** | 0.0147*** | 0.0574*** |
| | (5.7721) | (3.561) | (5.7403) | (3.6006) | (5.8131) | (4.2822) |
| SA_Part time | 0.0144*** | -0.0065 | 0.0142*** | -0.0068 | 0.0126*** | 0.0089 |
| | (6.4864) | (-0.5535) | (6.4061) | (-0.5835) | (5.4378) | (0.7272) |
| LA_experience | -0.0054*** | -0.005 | -0.0054*** | -0.0049 | -0.0055*** | -0.0048 |
| | (-9.1768) | (-1.6146) | (-9.1908) | (-1.5809) | (-9.336) | (-1.5244) |
| SA_experience | -0.0054*** | -0.0208*** | -0.0055*** | -0.021*** | -0.0053*** | -0.0214*** |
| | (-6.9213) | (-5.0094) | (-6.9533) | (-5.0501) | (-6.775) | (-5.1603) |
| LA_neighborhood | 0.023*** | 0.0077 | 0.023*** | 0.0079 | 0.0229*** | 0.0083 |
| | (9.8179) | (0.6242) | (9.8307) | (0.641) | (9.7767) | (0.6712) |
| SA_neighborhood | 0.0194*** | -0.0269* | 0.0193*** | -0.0266* | 0.0188*** | -0.0257* |
| | (6.8695) | (-1.7995) | (6.8362) | (-1.7847) | (6.6656) | (-1.7197) |
| LA_farming | 0.0238*** | 0.0994*** | 0.0238*** | 0.0984*** | 0.0235*** | 0.0924*** |
| | (4.3279) | (3.4255) | (4.3336) | (3.3916) | (4.2825) | (3.1826) |
| LA_market_share | 0.2802*** | -0.2722 | 0.2796*** | -0.2639 | 0.2657*** | -0.2131 |
| | (6.8645) | (-1.2624) | (6.8502) | (-1.2238) | (6.5057) | (-0.9874) |
| Dual_agent | 0.0015 | 0.0994*** | 0.0015 | 0.0987*** | 0.0018 | 0.0989*** |
| | (0.4815) | (6.0961) | (0.4991) | (6.0501) | (0.5906) | (6.0606) |
| LA_coagent | 0.0122*** | -0.0088 | 0.0122*** | -0.0089 | 0.0119*** | -0.0081 |
| | (6.594) | (-0.9021) | (6.6035) | (-0.9107) | (6.4813) | (-0.8312) |
| LA_Female | 0.0169*** | -0.0502*** | 0.0168*** | -0.051*** | 0.022*** | -0.0435*** |
| | (10.4414) | (-5.8836) | (10.3608) | (-5.9601) | (12.4256) | (-4.651) |
| LA_ever_bankrupt | | | | | 0.0044 | 0.0754*** |
| | | | | | (1.4411) | (4.6883) |
| LA_bankruptcy_event | | | -0.0195 | 0.1204 | -0.0232 | 0.0557 |
| | | | (-1.364) | (1.5951) | (-1.5987) | (0.7269) |
| LA_ever_bankrupt*LA_Female | | | | | -0.0293*** | -0.0434** |
| | | | | | (-7.3436) | (-2.0596) |
| LA_bankruptcy_event*LA_Female | | | 0.0069 | 0.1439 | 0.0311 | 0.182* |
| | | | (0.365) | (1.4393) | (1.621) | (1.7934) |
| SA_Female | 0.0227*** | -0.026*** | 0.0228*** | -0.0255*** | 0.024*** | -0.0069 |
| | (12.6778) | (-2.7558) | (12.7123) | (-2.6894) | (11.8099) | (-0.6469) |
| SA_ever_bankrupt | | | | | -0.0084*** | 0.0707*** |
| | | | | | (-2.7493) | (4.3957) |
| SA_bankruptcy_event | | | -0.0165 | 0.0211 | -0.0096 | -0.0318 |
| | | | (-1.2449) | (0.3012) | (-0.7131) | (-0.4475) |
| SA_ever_bankrupt*SA_Female | | | | | -0.0054 | -0.0779*** |
| | | | | | (-1.3167) | (-3.6194) |
| SA_bankruptcy_event*SA_Female | | | -0.0123 | -0.0562 | -0.0087 | 0.0016 |
| | | | (-0.7237) | (-0.6251) | (-0.5056) | (0.0172) |
| Property and neighborhood characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP code fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-quarter fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-Sq | 0.8159 | 0.1667 | 0.8159 | 0.1669 | 0.8162 | 0.1674 |
| Number of Obs. | 82817 | 82817 | 82817 | 82817 | 82817 | 82817 |

Table 7

Price-Liquidity Repeat Sales SUR Model - Bankruptcy variables estimates

This table reports coefficient estimates from SUR regressions with the natural logarithm of selling price *lnSP* and natural logarithm of days on market *lnTOM* . All models include competition and agent-level variables and year-quarter fixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| d_LA_FEMALE | 0.0166*** | -0.0617*** | 0.0167*** | -0.064*** | 0.0227*** | -0.0332 |
| | (3.8341) | (-2.759) | (3.864) | (-2.8561) | (4.7541) | (-1.3445) |
| d_LA_ever_bankrupt | | | | | 0.0182** | 0.1567*** |
| | | | | | (2.2585) | (3.765) |
| d_LA_bankruptcy_event | | | 0.0098 | -0.0425 | -0.0065 | -0.1728 |
| | | | (0.2468) | (-0.2065) | (-0.1607) | (-0.8287) |
| d_LA_ever_bankrupt*LA_Female | | | | | -0.0303*** | -0.1633*** |
| | | | | | (-2.8807) | (-3.0023) |
| d_LA_bankruptcy_event*LA_Female | | | -0.026 | 0.4133 | 0.0018 | 0.5499** |
| | | | (-0.4939) | (1.5174) | (0.0342) | (1.9944) |
| d_SA_Female | 0.0225*** | -0.0388 | 0.023*** | -0.0352 | 0.0265*** | -0.0111 |
| | (4.6572) | (-1.555) | (4.7397) | (-1.4048) | (4.8554) | (-0.3915) |
| d_SA_ever_bankrupt | | | | | -0.0058 | 0.1068** |
| | | | | | (-0.6812) | (2.4205) |
| d_SA_bankruptcy_event | | | 0.0277 | 0.4899** | 0.0325 | 0.4075* |
| | | | (0.6585) | (2.2482) | (0.7631) | (1.8465) |
| d_SA_ever_bankrupt*SA_Female | | | | | -0.0156 | -0.1107* |
| | | | | | (-1.4003) | (-1.9229) |
| d_SA_bankruptcy_event*SA_Female | | | -0.0571 | -0.6046** | -0.0455 | -0.5145* |
| | | | (-1.0985) | (-2.2459) | (-0.8627) | (-1.884) |
| Adj R-Sq | 0.461 | 0.1342 | 0.4609 | 0.1347 | 0.4616 | 0.136 |
| Number of Obs. | 11256 | 11256 | 11256 | 11256 | 11256 | 11256 |

Table 8

Price-Liquidity SUR Model - Crime variables estimates

This table reports coefficient estimates from SUR regressions with the natural logarithm of selling price *lnSP* and natural logarithm of days on market *lnTOM* . All models include property, neighborhood and census tract level variables, ZIP code and year-quarterfixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| LA_Female | 0.0169*** | -0.0502*** | 0.0169*** | -0.05*** | 0.0181*** | -0.0502*** |
| | (10.4414) | (-5.8836) | (10.4731) | (-5.8585) | (10.7662) | (-5.6494) |
| LA_ever_crime | | | | | 0.0034 | 0.0121 |
| | | | | | (0.8776) | (0.5959) |
| LA_crime_event | | | 0.0015 | 0.2988 | -0.0016 | 0.2825 |
| | | | (0.0429) | (1.6332) | (-0.0446) | (1.5364) |
| LA_ever_crime*LA_Female | | | | | -0.0161*** | 0.0067 |
| | | | | | (-2.891) | (0.2278) |
| LA_crime_event*LA_Female | | | -0.0446 | -0.1392 | -0.0296 | -0.1398 |
| | | | (-0.9638) | (-0.569) | (-0.6353) | (-0.5681) |
| SA_Female | 0.0227*** | -0.026*** | 0.0226*** | -0.0261*** | 0.0239*** | -0.0247** |
| | (12.6778) | (-2.7558) | (12.5881) | (-2.7607) | (12.7401) | (-2.491) |
| SA_ever_crime | | | | | 0.0088** | 0.0624*** |
| | | | | | (2.1694) | (2.9178) |
| SA_crime_event | | | -0.0477*** | 0.0604 | -0.0552*** | 0.0047 |
| | | | (-2.6549) | (0.637) | (-3.0143) | (0.0488) |
| SA_ever_crime*SA_Female | | | | | -0.014** | 0.028 |
| | | | | | (-2.3011) | (0.872) |
| SA_crime_event*SA_Female | | | -0.0187 | 0.0548 | -0.0063 | 0.0252 |
| | | | (-0.5857) | (0.3248) | (-0.1942) | (0.1472) |
| Property and neighborhood characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP code fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-quarter fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-Sq | 0.7374 | 0.1626 | 0.7374 | 0.1626 | 0.7374 | 0.1629 |
| Number of Obs. | 82817 | 82817 | 82817 | 82817 | 82817 | 82817 |

Table 9

Price-Liquidity Repeat Sales SUR Model - Crime variables estimates

This table reports coefficient estimates from SUR regressions with the natural logarithm of selling price *lnSP* and natural logarithm of days on market *lnTOM* . The sample includes all repeated transactions from Gwinnett County property records from 2004 through 2019. All models include competition and agent-level variables and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| d_LA_Female | 0.0166*** | -0.0617*** | 0.017*** | -0.0618*** | 0.0166*** | -0.0626*** |
| | (3.8341) | (-2.759) | (3.9283) | (-2.7617) | (3.6627) | (-2.6729) |
| d_LA_ever_crime | | | | | -0.0147 | 0.0444 |
| | | | | | (-1.5145) | (0.883) |
| d_LA_crime_event | | | 0.2175** | 0.1886 | 0.232** | 0.1543 |
| | | | (2.1836) | (0.3656) | (2.3231) | (0.2982) |
| d_LA_ever_crime*LA_Female | | | | | -0.0051 | 0.0416 |
| | | | | | (-0.3518) | (0.55) |
| d_LA_crime_event*LA_Female | | | -0.2708* | -0.2374 | -0.2728* | -0.2659 |
| | | | (-1.8835) | (-0.3188) | (-1.8902) | (-0.3556) |
| d_SA_Female | 0.0225*** | -0.0388 | 0.0223*** | -0.0396 | 0.0267*** | -0.0298 |
| | (4.6572) | (-1.555) | (4.6148) | (-1.5787) | (5.232) | (-1.1285) |
| d_SA_ever_crime | | | | | 0.0296*** | 0.0795 |
| | | | | | (2.816) | (1.4579) |
| d_SA_crime_event | | | -0.0033 | 0.0818 | -0.0277 | 0.0055 |
| | | | (-0.0706) | (0.3411) | (-0.5857) | (0.0226) |
| d_SA_ever_crime*SA_Female | | | | | -0.034** | -0.0657 |
| | | | | | (-2.1557) | (-0.8027) |
| d_SA_crime_event*SA_Female | | | -0.0734 | 0.8097 | -0.041 | 0.8498 |
| | | | (-0.6772) | (1.4423) | (-0.3757) | (1.5011) |
| Adj R-Sq | 0.461 | 0.1342 | 0.4611 | 0.1342 | 0.4616 | 0.1343 |
| Number of Obs. | 11256 | 11256 | 11256 | 11256 | 11256 | 11256 |

# Appendix

Table 1.A Variables definition

| Variable | Description and Data Source |
|---|---|
| Local Competition Ci | The number of houses listed for sale within 1 mile and with total living area within 20% of the subject property each day the subject property is on the market |
| Listing Density LDi | Local Competition divided by Time on the Market |
| *Transaction outcome* | |
| lnLP | The natural logarithm of one plus listing price. *Source*: MLS |
| lnSP | The natural logarithm of one plus selling price. *Source*: MLS |
| lnTOM | The natural logarithm of one plus days on the market. *Source*: MLS |
| *Property characteristics* | |
| lnSQFT_TOT | The natural logarithm of one plus total property area. *Source*: MLS |
| lnAGE | The natural logarithm of one plus property age in years. *Source*: MLS |
| lnBR | The natural logarithm of one plus number of bedrooms. *Source*: MLS |
| lnBAF | The natural logarithm of one plus number of full bathrooms. *Source*: MLS |
| lnBAH | The natural logarithm of one plus number of half bathrooms. *Source*: MLS |
| ATTACHED_TH | The indicator variable equal 1 for attached townhouse properties and 0 otherwise. Source: MLS |
| Fireplace | Number of fireplaces in the property. Source: MLS |
| Brickframe | The indicator variable equal 1 for properties with brick frame and 0 otherwise. Source: MLS |
| Brick3sided | The indicator variable equal 1 for properties with 3-sided brick frame and 0 otherwise. Source: MLS |
| Brick4sided | The indicator variable equal 1 for properties with 4-sided brick frame and 0 otherwise. Source: MLS |
| Brickfront | The indicator variable equal 1 for properties with brick front and 0 otherwise. Source: MLS |
| SHO_vacant | The indicator variable equal 1 for vacant properties and 0 otherwise. Source: MLS |
| *Neighborhood Characteristics* | |
| frac_below_18 | The fraction of population below 18 years old in a census tract. Source: American Community Survey, 2010-2020 |
| frac_65_over | The fraction of population over 16 years old in a census tract. Source: American Community Survey, 2010-2020 |
| frac_bach_higher | The fraction of population holding bachelor's degree or higher in a census tract. Source: American Community Survey, 2010-2020 |
| log_median_income | Median household income in the past 12 months in a census tract. Source: American Community Survey, 2010-2020 |
| *Buyer and seller characteristics* | |
| Investor_seller | The indicator variable equal 1 for properties sold by the company (rental properties). Source: MLS |
| Investor_buyer | The indicator variable equal 1 for properties bought by the company (properties bought for rent). Source: MLS |

Table 2.A

OLS Listing Price Model - Basic variables estimates

This table reports coefficient estimates for the key variables of interest from OLS regressions with the natural logarithm of listing price as the dependent variable. The sample includes all transactions from Gwinnett County property records from 2004 to 2020. All models include property, neighborhood and census tract level variables, ZIP code, year-quarter fixed effects. The full estimates are presented in the Appendix. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| Intercept | 7.9802***<br>(151.9185) | 7.9804***<br>(151.9353) | 7.9852***<br>(152.0305) |
| lnSQFT_TOT | 0.4779***<br>(62.2241) | 0.4779***<br>(62.2252) | 0.4772***<br>(62.1726) |
| lnAGE | -0.0812***<br>(-53.5537) | -0.0812***<br>(-53.5467) | -0.0815***<br>(-53.7328) |
| SHO_vacant | -0.0415***<br>(-16.3052) | -0.0416***<br>(-16.3283) | -0.042***<br>(-16.5017) |
| lnBR | 0.1224***<br>(15.2719) | 0.1226***<br>(15.2887) | 0.1234***<br>(15.3925) |
| lnBAF | 0.4025***<br>(51.3941) | 0.4024***<br>(51.3878) | 0.4022***<br>(51.4078) |
| lnBAH | 0.107***<br>(35.5844) | 0.107***<br>(35.5782) | 0.1069***<br>(35.5848) |
| ATTACHED_TH | -0.2248***<br>(-63.6201) | -0.2247***<br>(-63.612) | -0.2246***<br>(-63.6391) |
| FIREPLACE | 0.0683***<br>(35.6953) | 0.0683***<br>(35.6916) | 0.0681***<br>(35.6319) |
| Brickframe | 0.0554***<br>(34.603) | 0.0554***<br>(34.6024) | 0.0554***<br>(34.5989) |
| Brick3sided | 0.0218***<br>(13.172) | 0.0218***<br>(13.1728) | 0.0216***<br>(13.0758) |
| Brick4sided | 0.1139***<br>(32.922) | 0.114***<br>(32.9256) | 0.1138***<br>(32.8982) |
| Brickfront | 0.0096***<br>(5.896) | 0.0095***<br>(5.8776) | 0.0094***<br>(5.831) |
| STO_onestory | 0.0651***<br>(31.6498) | 0.0651***<br>(31.6384) | 0.065***<br>(31.5978) |
| AMEN_neighborhoodassoc | 0.0232***<br>(16.7224) | 0.0232***<br>(16.7124) | 0.023***<br>(16.6157) |
| AMEN_park | 0.0303***<br>(9.446) | 0.0303***<br>(9.4439) | 0.0304***<br>(9.4703) |
| AMEN_playground | 0.0019<br>(1.3509) | 0.0019<br>(1.3512) | 0.002<br>(1.4327) |
| AMEN_walkschool | 0.0057*<br>(1.8918) | 0.0057*<br>(1.8879) | 0.0055*<br>(1.8193) |
| AMEN_golfcourse | 0.0731***<br>(26.4751) | 0.073***<br>(26.461) | 0.073***<br>(26.4779) |
| AMEN_gatedcommunities | 0.1119***<br>(21.8081) | 0.1119***<br>(21.8146) | 0.1119***<br>(21.8168) |
| AMEN_clubhouse | 0.0446***<br>(20.4409) | 0.0446***<br>(20.4299) | 0.0445***<br>(20.3769) |

*Table 2.A - Continued*

| | (1) | (2) | (3) |
|---|---|---|---|
| | 0.1426*** | 0.1425*** | 0.144*** |
| frac_below_18 | (5.5711) | (5.5643) | (5.6301) |
| | 0.4868*** | 0.4865*** | 0.4836*** |
| frac_65_over | (15.3929) | (15.3838) | (15.3019) |
| | 0.5232*** | 0.5231*** | 0.5213*** |
| frac_bach_higher | (62.1303) | (62.1353) | (61.9586) |
| | 0.0035 | 0.0034 | 0.0033 |
| log_median_income | (1.4967) | (1.481) | (1.4166) |
| | -0.1416*** | -0.1418*** | -0.1417*** |
| Investor_seller | (-51.4111) | (-51.4571) | (-51.4779) |
| | -0.1033*** | -0.1031*** | -0.1024*** |
| DISTRESS_SALE | (-28.7447) | (-28.708) | (-28.5512) |
| | -0.2289*** | -0.2291*** | -0.2292*** |
| REO | (-57.8977) | (-57.9273) | (-57.9848) |
| ZIP code fixed effects | Yes | Yes | Yes |
| Year-quarter fixed effects | Yes | Yes | Yes |
| Adjusted R-Square | 0.7936 | 0.7936 | 0.7939 |
| Number of Observations | 124771 | 124771 | 124771 |

Table 3.A

Price-Liquidity SUR Model - Full estimates

This table reports full coefficient estimates from 3SLS regressions with the natural logarithm of selling price lnSP and natural logarithm of days on market lnTOM as the dependent variables. All models include ZIP code and year-quarter fixed effects. The last two rows report the total number of observations and adjusted R-squared of each regression. (***), (**), and (*) indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| Intercept | 7.6129*** | 0.3292* | 7.6142*** | 0.3186* | 7.6205*** | 0.2742 |
| | (227.8233) | (1.8654) | (227.8384) | (1.8049) | (228.076) | (1.5527) |
| LDi | -0.005*** | 0.0177*** | -0.005*** | 0.0177*** | -0.005*** | 0.0175*** |
| | (-14.9249) | (10.0554) | (-14.9198) | (10.0346) | (-14.862) | (9.9305) |
| lnSQFT_TOT | 0.4331*** | 0.2357*** | 0.4331*** | 0.2362*** | 0.4326*** | 0.2382*** |
| | (131.006) | (13.4995) | (130.991) | (13.527) | (130.9539) | (13.6446) |
| lnAGE | -0.1039*** | 0.087*** | -0.1039*** | 0.0871*** | -0.1042*** | 0.087*** |
| | (-66.6551) | (10.5676) | (-66.6456) | (10.5738) | (-66.8615) | (10.5646) |
| SHO_vacant | -0.0294*** | 0.0839*** | -0.0295*** | 0.0844*** | -0.0299*** | 0.0848*** |
| | (-12.4721) | (6.7349) | (-12.4968) | (6.7768) | (-12.6757) | (6.8079) |
| lnBR | 0.1379*** | 0.0446 | 0.138*** | 0.044 | 0.1384*** | 0.0422 |
| | (22.4503) | (1.3728) | (22.4601) | (1.3545) | (22.5411) | (1.2994) |
| lnBAF | 0.3688*** | 0.1573*** | 0.3688*** | 0.1574*** | 0.3683*** | 0.156*** |
| | (65.6118) | (5.2969) | (65.6095) | (5.3004) | (65.5746) | (5.2542) |
| lnBAH | 0.1005*** | 0.0998*** | 0.1005*** | 0.1001*** | 0.1003*** | 0.1001*** |
| | (39.4293) | (7.4096) | (39.4245) | (7.4351) | (39.3754) | (7.4335) |
| ATTACHED_TH | -0.2414*** | 0.0195 | -0.2414*** | 0.0196 | -0.2413*** | 0.0205 |
| | (-63.6843) | (0.9723) | (-63.6716) | (0.9767) | (-63.7206) | (1.0264) |
| FIREPLACE | 0.065*** | 0.0023 | 0.065*** | 0.0023 | 0.0648*** | 0.0025 |
| | (37.1429) | (0.2517) | (37.1396) | (0.2507) | (37.0502) | (0.271) |
| Brickframe | 0.039*** | 0.0125 | 0.039*** | 0.0127 | 0.0389*** | 0.0134 |
| | (22.8908) | (1.3933) | (22.8892) | (1.4137) | (22.8446) | (1.4954) |
| Brick3sided | 0.0339*** | 0.0251** | 0.0339*** | 0.0253** | 0.0335*** | 0.0262** |
| | (15.9531) | (2.2366) | (15.9569) | (2.2565) | (15.7946) | (2.3421) |
| Brick4sided | 0.1039*** | 0.1094*** | 0.1039*** | 0.1093*** | 0.1036*** | 0.1104*** |
| | (33.6797) | (6.7108) | (33.6772) | (6.7088) | (33.5912) | (6.7756) |
| Brickfront | 0.0172*** | -0.013 | 0.0171*** | -0.0125 | 0.017*** | -0.0115 |
| | (8.6972) | (-1.2433) | (8.6701) | (-1.1998) | (8.6037) | (-1.103) |
| STO_onestory | 0.0522*** | -0.0312*** | 0.0522*** | -0.0311*** | 0.052*** | -0.0312*** |
| | (25.517) | (-2.8902) | (25.5046) | (-2.8764) | (25.439) | (-2.8848) |
| AMEN_neighborhoodassoc | 0.0363*** | -0.0133 | 0.0363*** | -0.0134 | 0.0362*** | -0.013 |
| | (21.7003) | (-1.5084) | (21.7112) | (-1.5165) | (21.6593) | (-1.4776) |
| AMEN_park | 0.0277*** | 0.0537*** | 0.0277*** | 0.0539*** | 0.0277*** | 0.0538*** |
| | (7.7799) | (2.8535) | (7.7822) | (2.8657) | (7.7765) | (2.8616) |
| AMEN_playground | 0.0084*** | -0.0178* | 0.0084*** | -0.0177* | 0.0084*** | -0.0179* |
| | (4.5969) | (-1.8353) | (4.5926) | (-1.8284) | (4.6068) | (-1.8473) |
| AMEN_walkschool | 0.01*** | -0.0473*** | 0.0099*** | -0.047*** | 0.0099*** | -0.0472*** |
| | (2.9279) | (-2.6303) | (2.9228) | (-2.6172) | (2.8987) | (-2.6278) |
| AMEN_golfcourse | 0.0716*** | -0.0048 | 0.0715*** | -0.0042 | 0.0713*** | -0.0053 |
| | (21.0605) | (-0.2672) | (21.0441) | (-0.2358) | (21.001) | (-0.297) |
| AMEN_gatedcommunities | 0.1017*** | 0.3025*** | 0.1016*** | 0.3025*** | 0.1015*** | 0.3022*** |
| | (18.037) | (10.1615) | (18.0319) | (10.1615) | (18.032) | (10.1575) |

*Table 3.A - Continued*

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | lnSP | lnTOM | lnSP | lnTOM | lnSP | lnTOM |
| AMEN_clubhouse | 0.0468*** | 0.0566*** | 0.0468*** | 0.0567*** | 0.0466*** | 0.0567*** |
| | (17.8402) | (4.0858) | (17.8292) | (4.0931) | (17.7522) | (4.0939) |
| frac_below_18 | 0.092*** | -0.3172** | 0.092*** | -0.3147** | 0.0928*** | -0.3067** |
| | (3.2371) | (-2.1135) | (3.2395) | (-2.0975) | (3.2702) | (-2.0447) |
| frac_65_over | 0.3287*** | 0.3313* | 0.3292*** | 0.3326* | 0.3261*** | 0.352** |
| | (9.6848) | (1.8483) | (9.6998) | (1.8553) | (9.6161) | (1.964) |
| frac_bach_higher | 0.5155*** | -0.1106** | 0.5152*** | -0.1109** | 0.5132*** | -0.1082** |
| | (57.8253) | (-2.3488) | (57.7976) | (-2.3549) | (57.6038) | (-2.2984) |
| logedian_income | -0.0026 | 0.0258* | -0.0026 | 0.0264** | -0.0027 | 0.0268** |
| | (-1.0271) | (1.9401) | (-1.0362) | (1.9828) | (-1.0581) | (2.0158) |
| Investor_seller | -0.0968*** | 0.0815*** | -0.0969*** | 0.0826*** | -0.0966*** | 0.0829*** |
| | (-41.5824) | (6.6275) | (-41.6235) | (6.7128) | (-41.5157) | (6.7389) |
| Distress_Sale | -0.0812*** | 0.3024*** | -0.081*** | 0.3014*** | -0.0805*** | 0.2986*** |
| | (-22.5855) | (15.9227) | (-22.518) | (15.8698) | (-22.3899) | (15.7193) |
| REO | -0.1744*** | 0.0677*** | -0.1744*** | 0.0692*** | -0.1743*** | 0.0672*** |
| | (-53.6616) | (3.9454) | (-53.6586) | (4.0322) | (-53.6692) | (3.913) |
| ZIP code fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-quarter fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R-Sq | 0.8159 | 0.1667 | 0.8159 | 0.1669 | 0.8162 | 0.1674 |
| Number of Obs. | 82817 | 82817 | 82817 | 82817 | 82817 | 82817 |