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Does Personal Financial Distress Affect Workers' Productivity? Evidence from Real Estate Agents

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BY

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Of

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ACCEPTANCE

This dissertation was prepared under the direction of the Liuming Yang Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

Richard Phillips, Dean

DISSERTATION COMMITTEE

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ABSTRACT

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Committee Chair: Dr. Vincent Yao

Major Academic Unit: Department of Real Estate

The paper studies the direct effect of personal financial distress on workers' productivity and its spillover effects on their customers. Using the real estate brokerage industry as a setting and agents' bankruptcy filings as a proxy for personal financial distress, we first construct an empirical model that predicts the likelihood of personal financial distress at the individual by year level. After validating the model, we apply the constructed ex ante "financial distress score" to study its effect on agents' productivity. We find that both listing and sale prices are significantly lower and time on market is much shorter as the financial distress score increases while controlling for agents' fixed effects and other market and property attributes. These results suggest that financially distressed agents are more motivated to close the deal quickly at a lower price. In addition, we find that the less desirable sales outcomes induced by agents' financial distress spill over to homeowners' future buying activities. These owners subsequently buy smaller houses with much higher loan-to-value ratios.

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April 15, 2022

Abstract

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Keywords: Personal Financial Distress; Real Estate Agent; Productivity; Spillover Effect;

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1. Introduction

Intermediaries play a great role in our society, connecting buyers and sellers. Many producers do not sell products or services directly to consumers and instead use marketing intermediaries to execute an assortment of necessary functions to get the product to the final user. These intermediaries, including financial intermediaries, agents, and brokers, typically enter into longer-term commitments with the producer and make up what is known as the marketing channel. If intermediaries experience financial distress, it will affect the services provided to the buyer and seller. A good example is that financial intermediaries (i.e., banks) experienced a severe financial distress in 2008, which caused a systemic financial crisis and affected the real economy. Here, we extend this research topic by examining the determinants of real estate agents' financial distress as well as how this personal situation affects services provided by real estate agents to home sellers.

For several reasons, the real estate brokerage industry provides an excellent setting for studying the determinants and consequences of personal financial distress. First, we explore the important factors, such as total earned commission, working experience, disciplinary records, etc. that determine the level of real estate agents' financial distress, and further construct a "financial distress score". Similar to the previous empirical literature which had been conducted to identify corporate financial distress and which generated well-known measurements of the severity of firms' distress (i.e., Kaplan and Zingales (KZ) index, Whited and Wu (WW) index, and size-age (SA) index), we are trying to predict the severity of real estate agents' financial distress at the individual level. Second, unlike other working environments where employers set the working loads and employees do not have choices over their working hours and labor supply, real estate agents can set their own hours. Therefore, real estate agents' choice of working hours is a self-selection decision (Benjamin et al. 2007). Because that choice is discretionary for real estate agents, they could easily adjust their listing and selling strategy when facing negative financial shocks, in contrast with other industries where working hours are fixed. Third, the agency problem is more pronounced in the relationship between real estate agents and their clients[1] in the real estate industry compared with other settings, such as the relationship between innovation workers and firms (Bernstein, McQuade, and Townsend, 2021) or between teachers and students (Maturana and Nickerson, 2020). Most industries use a

[1]In this paper, we use "client" and "home seller" interchangeably, as we do "real estate agent" and "broker".

financial incentive to reduce the misalignment of incentives between principals and agents, but the financial incentive structure—that is, the commission structure—fails to mitigate the agency problem in the real estate market. The commission fee features a constant rate (5%–6% of sale price) both over different regions and over time. This percentage-based commission structure provides the agent only a small marginal benefit for extra effort (Yavas, 2007; Levitt and Dubner, 2014). For example, a $10,000 decrease in selling price only causes a $300 loss in commission fee but saves much effort for agents. Therefore, the real estate market provides a great setting for studies on agency problems. Fourth, we can observe productivity repeatedly for the same real estate agent over time, which enables us to exploit the variations within a real estate agent over time. Fifth, we can track the home sellers over time after their first sale and measure changes in house size and leverage when these home sellers subsequently purchase a second house. So, we can directly test the spillover effect from the impact of real estate agents' financial distress on themselves to the impact on the home sellers. Most home sellers use the proceeds from the sale of their previous house to pay for their next house purchase. If real estate agents cause losses for home sellers because of the agents' financial distress, home sellers may have to distort their purchase decision. For example, home sellers may have to obtain larger loans to pay for the houses and increase financial leverage due to the loss of sale price from their previous houses caused by distressed agents. Therefore, we can take a further step and compare the differences in house purchase decisions, such as the leverage decision and the house size decision, among home sellers whose houses are represented by agents with different likelihoods of financial distress.

We use personal bankruptcy filing to proxy for individuals' financial distress, following Maturana and Nickerson (2020). In this paper, we adopt a "financial distress score" approach to study the impact of personal financial distress on real estate agents' productivity. First, we construct an empirical model to predict the likelihood of financial distress for each agent at each year. The variables used for financial distress prediction, such as total earned commission, total commission growth, and working experience, are selected building upon a large corporate finance and household finance literature. Following Lamont et al. (2001), we use probit regression to construct a score consisting of a combination of these important factors that determine real estate agents' financial distress, which we call the "financial distress score". Second, we use financial distress score calculated from the prediction model in the first step to study the impact of personal financial distress on agents' behavior.

We have several challenges to finding the effect of financial distress on real estate agents' productivity. The first concern is that unobserved agent-level characteristics may drive our results. For example, different agents have different utility functions or different risk preferences. Agents who filed for bankruptcy may endogenously have a lower productivity. We overcome this question by conducting within-agents analysis so that we can fix the agents' time-invariant characteristics. The second concern is that local economy may both cause agents to be financially distressed and cause housing prices to move. To overcome this challenge, we include agents' location (zip code) by year fixed effects. Therefore, all our tests include real estate agent fixed effects to make sure all the analyses are conducted within individuals, and agents' location by year fixed effects to rule out the possibility that time-varying local factors drive our results. Our baseline result shows that the listing price and selling price of agent-represented houses is significantly lower and TOM is shorter when the likelihood of agents' financial distress increases. Specifically, we find listing price and sale price of agent-represented houses fall by 3.9% and 4% respectively and TOM decreases by 13.6% when the likelihood of financial distress increases from 0 to 1. Relative to mean, listing price and sale price of clients' houses drop by $9,633 and $8,840, respectively, but the clients' houses are sold about 14 days earlier if represented by agents who are financially distressed compared with non-distressed agents. Therefore, financially distressed agents sell clients' houses $8,840 lower than non-distressed agents but close the deal two weeks earlier. In other words, distressed agents forgo around $265 commission compared to non-distressed agents but received $6,365 commission two weeks earlier. These results are still robust when we add housing characteristics as well as housing location (county) by year fixed effects as control. The above results further confirm our hypothesis that personal financial distress makes real estate less patient for monetary reward, which leads to a decrease in time spent on housing-search-related tasks, further leading to lower listing prices and sale prices as well as shorter TOM, which is consistent with the prediction from behavioral finance theory where it highlights that a negative income event has impact on time discounting and makes people behave more impatiently.

We also conduct a battery of robustness checks to rule out other possible explanations and make sure our results are not driven by other confounding factors. For example, there may be concern that different brokerage firms may have different preferences in listing and selling decisions. Another concern may be that different agents' specialized market listing strategies (e.g., listing price) and listing times drive our results. To test the robustness of the results, we match the real estate agents from the top quintile financial distress score ranking to agents whose distress score ranking is in bottom quintile based on the brokerage firm they are working at, real estate markets they are specialized in, represented houses' listing price as well as listing time. The robust results assure us that the personal finance distress indeed leads to the decrease in productivity.

Last, we track the home sellers' future purchases and compare the decision made by home sellers represented by agents with different likelihoods of financial distress. We find home sellers whose sold house is represented by agents more likely to be financially distressed tend to purchase smaller houses and use higher leverage when they purchase their next houses. All the above results indicate the spillover of the negative effect of personal financial distress from real estate agents to home sellers.

Our paper contributes to several strands of literature. First, our paper is related to the literature on the measurement of financial distress. For example, extant corporate finance literature has mainly used investment–cash flow sensitivities (Fazzari et al. 1988), the Kaplan and Zingales (KZ) index of constraints (Lamont et al. 2001), and the Whited and Wu (WW) index of constraints (Whited and Wu, 2006) to measure firms' likelihood of financial distress. While there are many possible methods for measuring financial constraints, our paper is the first to construct a "financial distress score" at the individual level, and our discussion in this paper not only contributes to the measure of the financial distress severity at the individual level, but also instructs home sellers to identify and avoid potential distressed agents. Second, our paper extends the literature on the consequence of personal financial distress. Personal financial distress can affect household consumption (Mian et al. 2015), and inventors' productivity (Bernstein, McQuade, and Townsend, 2021), teachers' teaching outcomes (Maturana and Nickerson, 2020), career choice in the film industry (Cespedes, Liu and Parra, 2019), and financial advisors' misconduct (Dimmock, Gerken and Van Alfen, 2018). We complement this strand of literature in household finance by studying the role that real estate agents play in the housing transaction process and how real estate agents' financial distress affects their productivity and further impacts their clients. Third, our paper adds to the literature on the agency problem and conflict of interest between agents and clients in the real estate market. The existing literature mainly discusses the agency problem (Rutherford, Springer, and Yavas, 2005; Levitt and

Syverson, 2008a; Agarwal et al. 2019, Liu, Nowak, and Smith, 2020), steering (Levitt and Syverson, 2008b; Rutherford and Yavas, 2012; Han and Hong, 2016; Barwick, Pathak and Wong, 2017; Lopez, McCoy, and Sah, 2019), and agent competition (Hsieh and Moretti, 2003; Han and Hong, 2011; Barwick and Pathak, 2015) in the real estate market. We complement extant literature by analyzing principle-agent problems under personal financial distress settings and studying if agents' financial distress exacerbates principle-agent problems. Last, our paper contributes to the understanding of the spillover effects. Literature studies the spillover effect of house foreclosures (Harding, Rosenblatt, and Yao, 2009; Campbell, Giglio and Pathak, 2011; Anenberg and Kung, 2014; Gerardi et al. 2015), propagation or transmission of financial shocks through networks (Khwaja and Mian, 2008; Townsend, 2015; Barrot and Sauvagnat, 2016; Giroud and Mueller, 2019), and the mitigation of negative externality due to government bailout (Agarwal et al. 2015, 2017; Moulton et al. 2020). We complement the previous research by analyzing the spillover effect of agents' financial distress to clients, that is, home sellers. We ask if personal financial distress indeed affects agents' productivity and how it affects home sellers through the agent-client connection. Our results have potential implications for both policy makers and industry participants. This paper provides evidence for the negative effect of financial distress on productivity and finds the productivity reduction could amplify the negative effect from agents to their clients and cause negative spillover. Therefore, policy makers should be aware of this negative externality and realize that assistance to financially distressed individuals will extend the benefit beyond the static benefits for a particular person through their network connections. Also, this paper highlights important factors that are used for prediction of the likelihood of agents' financial distress ("financial distress score") and can instruct home sellers to identify distressed agents and avoid the losses those agents incur.

The paper proceeds as follows. Section 2 reviews the literature and develops our hypothesis. Section 3 introduces the background of this paper. Section 4 talks about the data and sample selection. Section 5 discusses the research design as well as the main results. Section 6 concludes.

2. Literature Review and Hypothesis

In this section, we review four strands of literature: the determinants and real effect of personal financial distress, the conflict of interest between agents and clients, and the externality effect of peers. We discuss the potential contribution of our paper to the existing literature and develop our main hypothesis on the effect of financial distress on real estate agents' productivity based on prior research and literature.

2.1. Determinants of Personal Financial Distress

The first strand of literature focuses on the determinants of financial distress. To study the role of financial distress, researchers are often in need of a measure of the severity of this distress. Corporate finance literature has already built mature and comprehensive distress indices, such as the Kaplan and Zingales (1997) index (KZ index), the Whited and Wu (2006) index (WW index), and the Hadlock and Pierce (2010) size-age index (SA index), but the study on determinants of financial distress at the individual level is an emerging field, which is divided into two parts: willingness-to-pay theory and ability-to-pay theory.

Neoclassical economic theory (Posner, 1974; Shuchman, 1977; White, 1991) argues that rational choices made by individuals are the central focus of the economic theory of bankruptcy. "The economic man" is assumed to act rationally by calculating costs and benefits to maximize his pleasure or wealth when making bankruptcy filing decisions. The theory expects individuals to file for bankruptcy protection when the economic incentives of bankruptcy will make them better off. When the benefits of filing bankruptcy exceed the related costs, the rational maximizer "economic man" would choose to file for bankruptcy. In the most recent paper, Mikhed, Scholnick and Zhu (2019) use option theory and life cycle to explain why individuals file for bankruptcy. They argue that bankruptcy is an American-style put option with a value that depends on households' risk attitude, elasticity of intertemporal substitution, and the discount rate. Their results indicate that households with lower net worth, households with more leverage in their balance sheet, and households with less income have a higher option value and, therefore, are more likely to file for bankruptcy. Empirically, Fay, Hurst, and White (2002) support the above theory and establish a framework to measure borrowers' financial benefit from bankruptcy filings. The factors that affect bankruptcy filing decisions include their unsecured debts, nonexempt assets, bankruptcy exemptions, and the costs of filing for bankruptcy, such as legal fees and limited access to credit in the future. The authors emphasize that households are most likely to enter bankruptcy when it is financially advantageous to do so.

Sullivan, Warren and Westbrook (1999) are the first to propose the ability-to-pay theory, which says borrowers file for bankruptcy when an unanticipated event occurs that reduces their ability to meet their loan payments. This theory is further developed by Sullivan, Warren, and Westbrook (2000), who argue that increases in credit card and mortgage debt and unexpected adverse events (such as unemployment, divorce, health problems, or medical debts) have reduced the ability of households to repay their debt and eventually compel them to file for bankruptcy. Empirically, some literature focuses on how personal income affects the likelihood of personal bankruptcy filing. For example, Barron and Staten (1997) find that income of consumers who filed for bankruptcy is significantly lower compared with that of non-filing consumers. Livshits et al. (2016) find that people who are less educated and have lower income as well as lower net worth are more likely to file for bankruptcy. Fisher (2005) reexamines the role of household income by using a greater number of explanatory variables in the Panel Study of Income Dynamics (PSID) and obtains a similar result. Other literature tests this theory by examining how a negative income shock affects the bankruptcy filing decision. Morrison et al. (2013) document that adverse health and medical expense shocks contribute to the likelihood of bankruptcy filing.

By comparing those two theories, we argue that being unable to pay or forced to file for bankruptcy can largely explain the personal bankruptcy decision-making in our setting due to three reasons. First, a series of literature documents that most people do not choose to file for bankruptcy even if they would benefit financially from doing so. For example, Athreya (2004) and Cohen-Cole and Duygan-Bump (2008) argue that people think about stigma attached to bankruptcy and that stigma could keep individuals from filing for bankruptcy even if it is financially advantageous to do so. Second, by directly comparing willingness to pay with ability to pay, Gan, Sabarwal, and Zhang (2012) also favor the ability-to-pay hypothesis than strategic filing. They find that most bankruptcy filings are due to the debtor's inability to repay. Third, our sample period is from 2000 to 2020, most of which is after the 2005 bankruptcy reform, which makes it harder for consumers to file for bankruptcy due to the increase in the filing cost and decrease in filing benefits. Less generous bankruptcy laws largely decreased the moral hazard attributable to the option to discharge debts as documented by White (2007), Indarte (2019), and Gross et al. (2019).

We complement this strand of literature by building an empirical model to explain and predict the likelihood of real estate agents' financial distress. Meanwhile, we follow Lamont et al. (2001) and construct a "financial distress score" to study the impact of personal financial distress on individuals' behavior.

2.2. Real Effect of Personal Financial Distress

The second strand of literature focuses on the real effect of financial distress. Financial distress has a negative impact on personal consumption. For example, Mian et al. (2015) investigate the consequences of deterioration in household balance sheets and find that the decline in housing wealth leads to a decrease in consumption. Maggio, Kalda and Yao (2019) also provide direct evidence on how debt relief benefits individuals and find that student loan debt relief increases borrowers' consumption. Financial distress also affects personal behaviors. For example, Pool et al. (2019) show that negative housing wealth shocks cause fund managers to reduce risk due to career concerns. Adopting a similar identification strategy, Bernstein, McQuade, and Townsend (2021) find negative housing wealth shocks to inventors translate into fewer patents and more patents with lower quality. Dimmock, Gerken, and Van Alfen (2018) find that advisors increase misconduct following declines in their homes' values. Cespedes, Liu, and Parra (2019) study how negative housing wealth shocks affect actors' career choice and finds that losses in housing wealth makes homeowners less likely to choose films with high reward. Using field study and focusing on financially constrained workers, Kaur et al. (2021) find that those who received cash increase productivity by 5.3%.

We complement this strand of literature in household finance by studying the role that real estate agents play in the housing transaction process and how financial distress of real estate agents affects their productivity and further impacts their clients.

2.3. Conflict of an Interest Between Agents and Clients

The third strand of literature focuses on the conflict of interest between agents and clients—the agency problem. The principal–agent problem is one of the oldest research topics in corporate finance (Weisbach, 1988; Geltner, Kluger and Miller, 1991). As an example of the principle-agent problem, the conflict of interest between real estate agents and clients in the real estate market has attracted more and more attention from researchers in recent years. Some studies discuss the incentive problem between agents and clients. Rutherford, Springer and Yavas (2005) find that agent-owned houses sell at a higher price but see no time-on-market difference. They attribute these results to agents' efforts. Similarly, Levitt and Syverson (2008a) find that agent-owned houses sell at a higher price and stay on the market longer, and they argue this is due to the agents' information advantage. Agarwal et al. (2019) found agents purchased their own houses at a lower offering price compared with other buyers. However, Liu, Nowak, and Smith (2020) document that the agent-owned premiums reported in the extant literature dissipate when textual information is included in the regression, and the authors think previous findings are subject to an omitted variable issue. Some studies examine conflict of interest by focusing on steering in the real estate market such as steering consumers to affiliated financial services (Lopez, McCoy, and Sah, 2019), to affiliated brokerages (i.e., in-house transactions) (Han and Hong, 2016), and to high-commission properties (Levitt and Syverson, 2008b; Rutherford and Yavas, 2012; Barwick, Pathak and Wong, 2017). In the mortgage market, loan product steering is also documented in the literature. For example, Agarwal et al. (2016) find that lenders steer borrowers to take out mortgage products with high interest rates. Gambacorta et al. (2017) also confirm the banks' steering effect, and they argue this effect varies based on household sophistication. Agarwal, Ambrose and Yao (2020) find that lenders steer borrowers into piggyback loans rather than letting borrowers purchase private mortgage insurance for loans with loan-to-value (LTV) greater than 80%. Some studies focus on the entry into as well as competition in the brokerage market. Three works (Hsieh and Moretti, 2003; Han and Hong, 2011; Barwick and Pathak, 2015) on the consequence of free entry of agents in the real estate market find that it led to cost inefficiency and welfare deduction. A cut in commission fee would result in fewer agents but more welfare for home buyers/sellers. Barwick and Wong (2019) further provide insight for why the commission fee does not change despite the increase in competition and why the failure of competition exists in the real estate agent market. Results are quite opposite in the mortgage market. For example, Robles-Garcia (2019) shows that competition among mortgage brokers facilitates the entry of new lenders, and her structure model estimate finds a ban on commissions leads to 25% decrease in consumer welfare.

We complement extant literature by analyzing principle-agent problems under agents' financial distress settings and studying if agents' financial distress exacerbates principle-agent problems.

2.4. Externality Effect of Peers

The fourth strand of literature focuses on the externality effect of peers. A good example is that there is a series of literature which focuses on the spillover effect of foreclosed properties. For example, Campbell, Giglio, and Pathak (2011) document that forced sales have spillover effects on the prices of local unforced sales. In particular, they that find that each foreclosure that takes place 0.05 miles away lowers the price of a house by about 1%. Harding, Rosenblatt, and Yao (2009) and Gerardi et al. (2015) document that one nearby foreclosed property leads to a 1% selling price discount of a non-distressed property transaction. Anenberg and Kung (2014) try to disentangle two sources, competition and disamenities, and find that the competitive pressure that a foreclosed property exerts on nearby sellers is an important source of the spillover effect. Also, the spillover effect through networks is a well-known strand of literature. For example, some literature studies how shocks are transmitted through bank-firm networks (Khwaja and Mian, 2008), internal firm networks (Giroud and Mueller, 2019), and supply chain networks (Barrot and Sauvagnat, 2016). Townsend (2015) documents non-IT firms which hold IT firm stocks are less likely to raise continuation financing due to the collapse of the technology bubble. Maturana and Nickerson (2020) document that students' passing rate decreases following a declaration of bankruptcy by their teachers. The research works on spillover effects help direct governments to make corresponding bailout policies. For example, due to negative spillover effects of foreclosure, the U.S. government initiated programs during the financial crisis to avoid foreclosure and help "underwater houses". The Home Affordable Refinance Program (HARP) and the Home Affordable Modification Program (HAMP) are two of the most important policies introduced by the U.S. government during the financial crisis. Agarwal et al. (2015, 2017) evaluate those two policies and find there is an increase in consumer spending following them. Moulton et al. (2020) finds that there is an increase in wages as well as employment after the receipt of mortgage payment subsides, another federal foreclosure program.

We complement the previous research by analyzing the spillover effect from agents to clients, that is, home sellers. We ask if financial distress indeed affects agents' productivity and how it spills over to home sellers through the client-agent connection.

2.5. Main hypotheses

We are trying to come up with two competing hypotheses. First, personal financial distress may boost the productivity of real estate agents. He or she may want to work harder to get out of financial distress and make up for the lost wealth so that he or she would increase the labor supply to make more commissions based on reference income and loss aversion theory documented in the literature (Rizzo and Zeckhauser, 2003; Goette et al. 2004).

Second, behavioral economics research argues that negative income shocks have impact on time discounting and makes people behave more impatiently when making financial decisions. For example, in Vietnam, Tanaka, Camerer, and Nguyen (2010) find evidence suggesting that income has a causal effect on an experimentally measured discount rate. Using a similar approach in Ethiopia, Di Falco, Damon, and Kohlin (2011) show that severe droughts led to increases in the discount rate. Also, focusing on low-income households in the U.S., Carvalho, Meier, and Wang (2015) show that before a payday, participants are found to be more present-biased in intertemporal choices about monetary rewards. So, based on previous literature, we hypothesize that financial distress makes real estate less patient for monetary reward, which leads to the decrease in time spending on housing-search-related tasks, further leading to lower listing price and sale price as well as shorter TOM.

Therefore, based on two competing hypotheses above, the effect of personal financial distress may be an empirical question.

3. Background

Real estate agents play a large role in real estate transactions, wherein the asset is illiquid, heterogenous, and traded in decentralized markets unlike stock markets. Home selling is a time-consuming process, which includes determining the asking price, advertising houses, matching, and showing houses as well as negotiating prices. Similar issues for the home buying process include visiting houses, negotiating offers, obtaining a mortgage, and closing the deal. Therefore, most home sellers and home buyers hire an agent to facilitate the buying and selling process. According to the

2019 National Association of Realtors Profile of Home Buyers and Sellers[2], 89% of all buyers/sellers purchased/sold their home through an agent, an increase of 20 percentage points compared with 69% in 2001, which indicates that real estate agents still play a great role in the Internet era. Real estate agents have access to the Multiple Listing Service (MLS) database and, therefore, can easily improve this matching process. For example, working as a listing agent, the agent advises how much the home seller should list the house for (listing price) on the website, matches and searches for buyers, negotiates the price, and closes the deal based on detailed property information from MLS.

The entry barrier for real estate agents is low despite the important role they play in the real estate market. For example, to become an agent in Georgia, you just need to go through two steps: first to complete 75 hours of Georgia Real Estate Commission-approved real estate education and, second, to take the Georgia Salesperson Licensing Exam. According to statistics from NAR[3], there were about 1.39 million real estate agents in the U.S. in 2019, an increase of 40% compared with 1 million real estate agents in 2011.

Agents' compensation mainly comes from the commission fee. Normally, a seller will pay 5%–6% of the sale price as a commission fee to the listing agent at the close of escrow. The commission fee is evenly split[4] between listing and buying agencies. Agents may submit a portion of the commission to their brokerage firm if they work for one. According to a report from the National Association of Realtors, \$5.34 million in homes were sold in 2019 and total commission fees added up to \$0.3 million in 2019. The high revenue earned by real estate agents attracts more and more people and firms entering this market.

A caveat of this paper is that results are estimated using transaction data and real estate agents' data from Georgia, most of which are in the Atlanta market. How valid are these results outside of the Atlanta market? The answer to this question boils down to how representative the Atlanta market is of other localities within the U.S. To understand the extent to which results from the Atlanta market generalize, it is crucially important to know how comparable the Atlanta market is to other locations in the United States in terms of its housing market, local demographics, and the real estate agent labor market. Table 1 compares the Atlanta market with the other top nine

[2] https://www.nar.realtor/sites/default/files/documents/2020-generational-trends-report-03-05-2020.pdf

[3] https://www.nar.realtor/research-and-statistics/quick-real-estate-statistics

[4] https://www.forbes.com/sites/forbesrealestatecouncil/2018/06/06/first-timer-faq-how-do-real-estate-commissions-work/

metropolitan areas in the U.S. as well as the whole nation. For the real estate market in 2018, for example, the median housing price in Atlanta is around $200,000, which is very close to national median price of $205,000. Housing prices in other markets are either much higher or lower compared with the national average. 90.9% of housing units in Atlanta are occupied, compared with 87.8% in the U.S., and more than 60% of occupied housing units in both Atlanta and the U.S. are single-unit detached houses. In addition, the owner-occupied housing share in Atlanta and the nation as a whole are nearly identical (63.1% in Atlanta vs. 63.8% in the U.S.). For demographics, the median age in Atlanta is a little bit younger than the national median age. The ratio of educated people in Atlanta is very close to the national ratio. And earnings in Atlanta are almost the same as those in the nation in terms of both median and mean. Therefore, the income-to-house price ratio is very similar when comparing the Atlanta market with the nationwide market. Although earnings in Phoenix are also almost identical to the national average, housing prices are relatively higher there than the national average. For the real estate agent job market, Atlanta has the highest employment level in the U.S. as of May 2019[5]. In addition, the median/mean hourly wage in Atlanta is $23.30/$27.10 per hour[6], which is very close to the national median/mean hourly wage: $23.53 vs. $29.83. Judging from above evidence, the Atlanta market looks representative of the U.S. average from three aspects: the real estate transaction market, demographics, and the real estate agent job market.

[insert Table 1]

4. Data and Sample Construction

Our data mainly comes from three resources: GAMLS, Bankruptcy Records as well as ZTRAX data. We give the detailed information of three datasets and present how we match those three datasets together.

[5] https://www.bls.gov/oes/current/oes419022.htm(9)
[6] https://www.bls.gov/oes/current/oes12060.htm

4.1. Datasets

4.1.1. GAMLS Data

We get MLS data in Georgia from GAMLS.com. GAMLS data includes all houses that were listed in GAMLS.com whether they were sold or not. We have property physical characteristics in the hedonic model, such as address of the property, house and lot sizes, and number of bedrooms and bathrooms, as well as listing information, such as listing date, listing price, sale price, closing date, and time on market. Most importantly, if the house is sold through real estate agents, the data contains agent information such as name, agent ID (which is coded in GAMLS), and the office where they work. Following Rutherford, Springer and Yavas (2005), we mainly focus on the agency problem between the listing agent and home sellers since the listing agent is more likely to determine how much a house is initially listed for, how much it is sold for, and how long it stays on the market. Also, the agent, 99% of the time, is the agent of the seller[7]. We focus on agent-represented home sales, and we only keep single-family detached home listings with a valid real estate agent name from January 1, 2000, to October 1, 2020.

4.1.2. Bankruptcy Records

We use Chapter 7 and Chapter 13 bankruptcy records filed in Georgia to proxy for individuals' financial distress. Bankruptcy filings in Georgia are also representative considering that both the total number and the number per 1,000 people of bankruptcy filings rank in the top 5 states in the U.S[8]. We obtain bankruptcy records from the Georgia Northern Bankruptcy Court from the Public Access to Court Electronic Records (PACER) system. While there are three bankruptcy districts in Georgia, we only get a fee-exemption access to the Georgia Northern Bankruptcy Court in the northern districts as depicted by Figure 1. Although our sample only covers one of three districts in Georgia, we argue that the bankruptcy filings in the Georgia Northern Bankruptcy Court are representative in Georgia since the counties with the most personal bankruptcies (Fulton, Dekalb, and Gwinnett) are all located in this district. Most importantly, the district includes the Atlanta

[7] https://knowledge.wharton.upenn.edu/article/the-subprime-blame-game-where-were-the-realtors/
[8] https://www.fool.com/the-ascent/research/personal-bankruptcy-statistics/

market, where most real estate agents are located and most housing transaction activities in Georgia happen.

[insert Figure 1]

Bankruptcy data contains filer information including debtor's name and address as well as case information including filing date from January 1, 2000, to November 30, 2020, chapter type, and creditor name, etc. We also complement our bankruptcy record filings from PACER with the Integrated Bankruptcy Database (IDB)[9] to get the income and debt amount information of each bankruptcy case. We link these two datasets with a unique identifier: case number.

4.1.3. ZTRAX Data

We use the Zillow Transaction and Assessment Dataset (ZTRAX) from January 1, 2000, through August, 1, 2020. It contains two main parts: the assessment record and the transaction record.

In the transaction record, we have transaction information such as transaction price, transaction time, non-arm's-length transaction indicator[10], mortgage information (cash sales or financed by mortgage, as well as the amount of the mortgage), buyer's name, and seller's name. The assessments record is originally generated by the county assessor's office and contains physical characteristics of houses including the property type (e.g., single-family houses, condominiums), house size (gross living areas in square feet), lot size in square feet, property age based on the year built, occupancy status (e.g., owner-occupied or investment), garage, and location. The transaction and tax assessments records are joined by the parcel ID. We only keep single-family or inferred single-family houses transactions in Georgia.

[9]https://www.fjc.gov/research/idb

[10]Non-arm's length transactions are those that happen between two individuals that have a relationship. A good example is a transaction between two family members. Normally, the transaction price in a non-arm's-length transaction does not reflect market prices, thus we exclude all these transactions based on Zillow's internal code.

4.2. Matching Across Different Datasets

4.2.1. Match GAMLS to Bankruptcy Data

Figure 2 shows the logic of how we merge the three datasets. We first describe how we merge the GAMLS listing data to bankruptcy files. The challenge of this merge is that there is no common field or unique ID between those two datasets for us to link with. We take advantage of real estate member data from GAMLS.com. That data contains information about all real estate agents registered in GAMLS, such as license number, first and last name, and firm where they work. Most importantly, it has the address information of real estate agents. We match the GAMLS data with real estate member data according to the unique identifier, AgentID[11]. After matching, we get GAMLS-member data, which contains both listing information and real estate agent information. Then, we match the GAMLS-member data to bankruptcy record data based on the methodology from Maturana and Nickerson (2020). We exactly match zip code, street number of the address, and last name between GAMLS-member and bankruptcy record data. We also create a dummy variable, spouse, equal to 1 if we only match the last name[12] between the two datasets. Our main analysis relies on this GAMLS-member-bankruptcy merged data.

[insert Figure 2]

4.2.2. Match GAMLS to ZTRAX Data

Next, we describe how we merge the GAMLS listing data to the transaction data from ZTRAX. The listing data contains the property's street address, zip code, closing date (the date when home buyer and home seller completed the transaction), transaction price, property type, number of bedrooms, and number of bathrooms of each listing. However, GAMLS does not have buyer's name or seller's name, which are used to track individuals' purchase decision and mobility over time. The transaction data from ZTRAX contains the property's street address, recording date, transaction price, buyer's name, and seller's name but does not have agent information or listing information. The address in the transaction data from Zillow is standardized, since Zillow directly gets the data

[11] AgentID is not necessarily the same for a same agent across time since an agent may move or change companies. Therefore, AgentID is based on the agent's name, address, and company where they work. Instead, license number is unique for an agent, and we use license number to uniquely identify agents.

[12] In this case, the bankruptcy was most likely filed by the agents' spouse.

from a county office. In contrast, the GAMLS data does not have a clean and standardized address format since the information in GAMLS is manually entered by a listing agent. To overcome this problem, we formalize the address in GAMLS and parse it into street number, street name, and zip code. We do same thing for ZTRAX data. Then, we use the join-by match method to match listing data with ZTRAX data based on street number, street name, and zip code. To make sure our match is accurate and precise, we only keep the unique matches meeting two restrictions: First, the difference of the sold price from two datasets is less than $500 and the difference of the sold date (close date in GAMLS and recording date in ZTRAX) is less than 1 month. The matched dataset is called GAMLS-ZTRAX data. By merging those two datasets, we can identify which home sellers' houses are represented by financially distressed agents and which are not.

4.2.3. Match Within ZTRAX

Finally, we track the purchase activity of home sellers following Buchak et al. (2020). First, we extract the unique seller names as well as unique buyer names from transaction records between January 2000 and May 2020 from ZTRAX in each market (Atlanta, Rome, Newman, and Gainesville). Second, we start with seller names in the year 2000 by each city. We match the seller name to the buyer name in the current year and next one year (e.g., buyer name in year 2000 and in year 2001) to check if home sellers buy a house within two years after the sale. We use exact match in the last name and fuzzy match (reclink in Stata, keeping the match score larger than 0.8) in the first name. We keeping doing this until we reach the year 2020, and we call this sample as ZTRAX-Track. Once we have this matched sample, we can track and compare the housing characteristics as well as loan amount among home sellers represented by different agents.

Our analysis on the spillover effect from financially distressed agents to home sellers is based on ZTRAX-Track data.

4.3. Final Sample

Our main analysis is based on GAMLS-member-bankruptcy merged data. We identify 1,575 real estate agents who filed for bankruptcy in total as the treated sample.

As we mentioned in the introduction, we adopt a "financial distress score" approach to study the impact of personal financial distress on real estate agents' productivity. We first construct an empirical model to predict the likelihood of financial distress for each agent and then use the financial distress score calculated from the prediction model as a first step to test our research question. This approach is applied to all real estate agents in the market, including 1,575 real estate agents who filed for bankruptcy and 26,969 real estate agents who have never filed for bankruptcy[13]. Table 2 gives the detailed information of variables used for constructions of the financial distress prediction model along with literature support, economic meaning, and how we measure each variable in the dataset. We also give the summary statistics for the variables we use for financial distress prediction in Table 3 Panel A. For example, the median of commission earned per year is $51,120, which is close to the median value reported by the Census Bureau, and commissions experienced a small positive growth (0.162%) in our sample period. Agents in our sample have 11 years' experience on average, and around 3% of agents and 5% of real estate firms in our sample ever had disciplinary records. We also report the correlation matrix in Table 3 Panel B to identify possible multicollinearity in the financial distress prediction regression model. We found our variables used for financial distress prediction have weak correlations between each two variables except three: agent commission, commission growth, and commission rank within same office. Therefore, we will add each variable into the prediction model and select one that has the highest explanatory power.

[insert Table 2 & 3]

5. Research Design and Result

5.1. Empirical Design

We design a two-step regression in the "financial distress score" approach. In the first step, we construct a financial distress prediction model with the factors we discussed in 2:

$$if(Distress_{i,t}) = \beta \times f(X_{i,t-1}) + \epsilon_{i,t}, \tag{1}$$

[13]Due to concern that some real estate agents have other primary occupations, as mentioned by Barwick and Pathak (2015), we only keep agents with at least 2 years listing history and at least 1.5 listings per year.

On the left-hand side in equation (1), $if(Distress_{i,t})$ is a dummy variable which indicates whether or not agent i in year t filed for bankruptcy (our proxy for financial distress). The value equals to 1 if an agent i in a given year t files for bankruptcy and 0 otherwise. $X_{i,t-1}$ on the right-hand side are the vectors used for financial distress prediction, such as total commissions earned by agent i in year t-1, etc. By doing so, we can assign a predicted financial distress score to each agent each year in our dataset and allow us to gather a wide range of values for financial distress[14].

In the second step, we study the impact of financial distress on a series of outcomes and estimate the following regression:

$$Outcome_{i,j,t} = \beta \times \widehat{Distress\ Score}_{i,t} + \theta_i + \delta_{a,t} + X_j + \gamma_{m,t} + \epsilon_{i,j,t}, \tag{2}$$

In equation (2), the observation unit is the agent(i)-property(j)-year(t) level. θ_i is agent fixed effects, $\delta_{a,t}$ is agent location (zip code) x year fixed effects, X_j is property attributes, $\gamma_{m,t}$ is property market (county) x year fixed effect. The primary independent variable we are interested in is $\widehat{Distress\ Score}_{i,t}$, which is the predicted likelihood of financial distress (a continuous variable) calculated from equation (1). We also call this the "financial distress score" in this paper. Our main outcome variable of interest includes listing price, sale price, time on market, probability of sale, and number of listed and sold houses. We add agents' zip code x year fixed effects to eliminate time-varying local confounding factors. Most importantly, we control for individual fixed effects, θ_i, to make sure our comparison is within individuals. Finally, we can observe the characteristics of each property and add those as control X_j.

5.2. Baseline Results

We first report the results (simple probit regression results) of the prediction model for agents' financial distress in Table 4 Panel A from equation (1). From Column (1) to Column (7), we see that higher earned total commission, higher commission growth, higher commission ranking within an office, longer experience in the housing market, working in a larger firm, higher house price index

[14]For example, some agents may be financially distressed but have not reached a point to file for bankruptcy. Therefore, the "financial distress score" approach can help us broaden our research sample and identify those agents who have a high likelihood of financial distress but do not actually file for bankruptcy.

growth, and ever having a disciplinary record are associated with a lower likelihood of bankruptcy filing, which aligns with our expectation. By comparing the Pseudo R^2 in the first three columns, we choose agents' total commission instead of commission growth and average ranking (recall that those three variables are highly correlated as Table 3 Panel B shows) to add into our final prediction model to avoid the multicollinearity problem. Column (8) reports our final prediction model with all selected predictive variables. The multiple probit regression result shows that the signs of the coefficients of the predictive variables are consistent with the simple probit prediction model from Column (1) to Column (7), and the magnitude does not change too much compared with the simple probit regression, which indicates the variables we chose for financial distress prediction are weakly correlated between each other.

We also validate the accuracy and predictive power of our financial distress prediction model using two tests. First, we calculate the average actual bankruptcy rate over quintiles of predicted probability after we assign a financial distress score (predicted probability) to each agent each year based on the regression result in Table 4 Panel A Column (8), and we compare the actual rate to the predicted rate in five groups. As presented in Table 4 Panel B, the distress score for each agent in each year is ranked from lowest to highest by five groups, and Column (4) and Column (6) report the average predicted probability and actual bankruptcy rate separately in five groups. In each bin, we see the average predicted probability rate is very close to the average actual bankruptcy rate. Second, we do in-sample and out-of-sample tests to see if the model works or not. Specifically, we randomly select half of samples for probit regression, and we apply the model derived from the selected half sample to another half sample to calculate the predicted value. Then, we draw the scatter plot between the predicted value versus the actual value to check the correlation. As shown in Figure 3 Panel A, the correlation of predicted value and actual value is very high. We also select a sample from years 2000 to 2012 to build the model and apply this model to calculate the predicted distress scores from year 2013 to 2020. The high correlation between predicted value and actual value as Figure 3 Panel B shows further validates our model's prediction power. In sum, the average comparison and in- and out-of-sample test further validate our prediction model and assure us that our financial distress model has good predictive power.

[insert Figure 3]

Then, in the second step, we test the impact of financial distress on several outcome variables, such as listing price, sale price, TOM, etc. We first did a univariate analysis to directly test the relationship between financial distress score and outcome variables we are interested in from Table 4 Panel B. We calculate the average listing price, sale price, TOM, and other housing characteristics over quintiles of predicted probability and check the correlation between the financial distress score and outcome variables without adding any controls. As presented in Table 4 Panel B, we find that the average listing price, sale price, and TOM decrease when the likelihood of financial distress increases, which shows that financial distress makes agents less patient and has a negative impact on their productivity. Financial distress seems to have no significant impact on the probability of sale. There may be concern that this analysis does not account for the heterogeneity of housing characteristics sold by different agents. We calculate average property age, number of beds, number of baths and house size over quintiles of predicted probability, and we do not find any significant increase or decrease when financial distress score changes. We also calculate the predicted listing/sale price with a hedonic model (what the price should be) and get the ratio of actual listing/sale price to predicted listing/sale price so that we can consider the effect of housing characteristics. The pattern between financial distress score and ratio of actual listing/sale price to predicted listing/sale price as presented in Table 4 Panel B further confirms the negative relationship between financial distress and agents' productivity.

[insert Table 4]

Preliminary results in Table 4 Panel B give us a simple analysis between financial distress and outcome variables, but it does not consider other controls that may affect our results, such as housing locations and time trend. Therefore, we formally test how personal financial distress affects agents' productivity by running regression (5) with all housing characteristics and fixed effects as controls. We start our analysis about the impact of personal financial distress on productivity with listing price as an outcome variable in Table 5. In Column (1), we add agent fixed effects and agents' location by year fixed effects with all hedonic controls, and the result shows that the listing price drops by 4.8% on average when the likelihood of financial distress increases by 100%. This regression does not account for the houses' locations and transaction times. Therefore, we add housing location fixed effects and listing year-quarter fixed effects separately, and the magnitude drops as Columns (2) and (3) show. Our Column (4) shows the result with all controls, including agent fixed effects, agents' location by year fixed effects, houses' location fixed effects, and listing year-quarter fixed effects, and the result shows that listing price of agent-represented houses falls by 3.9% if the likelihood of financial distress increases from 0 to 100%, which indicates that financial distress makes real estate agents less likely to list the property at a higher price. By comparing the coefficients across those four specifications, we find the coefficients of our prediction variables do not have a significant change, which indicates that much of the variations of the outcome variable are absorbed by individual fixed effects. Table 6 Column (4) shows the sale price decreases by 4% when the likelihood of financial distress increases by 100%, which indicates that financial distress makes real estate agents less likely to sell the property at a higher price. Table 7 Column (4) presents that the TOM is also lower when the likelihood of financial distress increases. We do not find probability of financial distress has the significant impact on sale probability and numbers of listed and sold houses from Column (1) to Column (4) in Table 8. Figure 4–6 visually show the negative relationship between listing price, sale price, and TOM with financial distress score.

[insert Figure 4-6; Table 5-8]

Our results above are consistent with our main hypothesis that financial distress makes real estate less patient for monetary reward, which leads to the decrease in time spending on housing-search-related tasks, and further leads to lower listing price and sale price as well as shorter TOM.

5.3. Robustness Tests

We perform several other tests to make sure that the negative effect on real estate agents' productivity is driven by financial distress rather than other confounding factors.

Different brokerage firms where real estate agents are working may prefer to list and sell houses with different prices. To rule out this possibility, we match the real estate agents from the top quintile financial distress score ranking to agents whose distress score ranking is in the bottom quintile based on the brokerage firms they are working at. We find a similar negative effect of financial distress on sale price when comparing within same brokerage firm as Column (1) to (3) in Table 9 Panel A show.

We are also concerned different housing markets may drive our results. To rule out this possibility, we match the real estate agents from the top quintile financial distress score ranking to agents whose distress score ranking is in bottom quintile based on the primary market specialization in Column (4) and Column (6). We can see similar results are still there, which helps us rule out that the different characteristics of housing markets drive our results. Some may be concerned that financially distressed agents may have a different listing strategy. For example, they may choose houses at different locations, different listing times, and different listing prices. To rule out this hypothesis, we match the real estate agents from the top quintile financial distress score ranking to agents whose distress score ranking is in bottom quintile based on the property listing market, listing time, and listing price separately. The regression results are reported in Column (1) to Column (5) in Table 9 Panel B. We still obtain significant and negative results, which rules out the possibility that different listing strategies drive our results. This test also helps us explain how much of the TOM reduction found in Table 7 is attributable to lower list prices versus agent efforts. The results presented in the last column of Table 9 Panel B indicate that after matching the listing price, the effect magnitude of distress on TOM is -0.117 after eliminating the lower listing price effect compared with -0.136 without matching. Therefore, the TOM reduction is around 14% due to lower listing price and 86% due to the agent's effort in pushing the deal to close as quickly as possible from our baseline results.

Finally, real estate agents in different real estate market conditions may have different reactions to personal financial distress. Table 9 Panel C tells us that the real estate market bust exacerbated the negative effect of financial distress on sale price while the effect is smaller in the boom.

[insert Table 9]

5.4. Spillover Effect

We documented that sale price of the agent-represented houses falls by 4% when the likelihood of real estate agents' financial distress increases by 100%. And since the real estate agents' financial distress has a negative effect on the sale price of clients' houses, this negative effect could directly affect home sellers through the agents-clients network and lead home sellers to suffer from this loss. Since most home sellers use the proceeds from a house sale to pay for their next house, we want to study how the loss caused by financially distressed agents distorts home sellers' future purchase decision. The data we are using in this section is ZTRAX-Track data where we can track the purchase decision of a home seller following Buchak et al. (2020). Since we require individuals to have a purchase record after they sold the houses from our baseline sample, the small sample in this section makes us unable to implement panel regression by adding fixed effects. Instead, we design the cross-section regression as follows:

$$Purchase\ Outcome_{i,t} = \beta \times \widehat{Distress\ Score}_{j,t-1} + X_i + \gamma_{m,t} + \epsilon_{i,j,t}, \tag{3}$$

Our outcome variable includes a dummy variable indicating if the home seller takes a loan for their second house purchase, loan size, housing price, housing size, and leverage of the second house. The main variable of interest is $\widehat{Distress\ Score}_{j,t-1}$, which indicates that the home sellers' first house is sold by agent j with distress score t-1. So, in equation (3), we compare the difference of the purchase decision between the home sellers represented by agents with different likelihoods of financial distress.

Table 10 reports the regression results. Column (1) shows that the home sellers represented by financially distressed agents are more likely to use a loan when they purchase the second house. Columns (2), (3), and (4) focus on loan size, house price, and loan-to-value ratio. The regression results show that home sellers are more likely to choose a larger loan and a larger loan-to-value when their first house was sold by an agent with a higher likelihood of financial distress. We also discuss the house size and lot size decision in Column (5) and Column (6), and we find that home sellers whose first house was sold by an agent with a higher likelihood of financial distress are more likely to purchase a smaller house. The evidence above shows that the negative effect of agents' financial distress spills over from the real estate agent to the home seller and that the home seller has to downsize their house choices and increase the leverage to pay for their next house if their first house is represented by a distressed agent.

Our findings in this section highlight the spillover effect and amplification of negative events from one to another. The results also provide evidence that assistance for financially distressed individuals or firms may stop this negative externality and provide benefit beyond the static benefits for just a particular participant in the assistance program.

[insert Table 10]

6. Conclusion

This paper investigates how financial distress affects workers' productivity. Using the real estate brokerage industry as a setting and filing of bankruptcy as a proxy for personal financial distress, we find that real estate agents' productivity is significantly lower when their likelihood of financial distress increases. Higher likelihood of agents' personal financial distress is associated with lower listing price and sale price as well as shorter time on market of the agent-represented houses. The above results are also robust when our analysis uses matched-sample-based agent characteristics and property characteristics. These findings are consistent with the prediction from behavioral economics research. Personal financial distress makes real estate less patient for monetary reward, which leads to the decrease in time spending on housing-search-related tasks and quick selling with a lower price.

Finally, our results also show the spillover effect from one to another. Most home sellers use the proceeds from a house sale to pay for their next house. And home sellers may have to downsize their house choices or obtain larger loans to pay for their next house due to the loss caused by financially distressed agents. Consistent with our conjecture, we find that home sellers are more likely to choose a larger loan-to-value ratio and purchase a smaller house when their houses are sold by a financially distressed agent.

Our results also have some implications for policy makers. This paper provides evidence for negative effect of financial distress on productivity and finds the productivity reduction could amplify and cause a negative spillover on clients through the agents-clients network. Policy makers should be aware of this negative externality and realize that reduction in financial distress will extend the benefit beyond the static benefits for a particular person through the network connection.

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Table 1 Comparison among Atlanta and Other CBSAs

	U.S.	Atlanta	Chicago	Dallas	Houston	Los Angeles	Miami	New York	Philadelphia	Phoenix	Washington
Housing Market											
Median Housing Price	$204,900	$199,200	$231,400	$193,100	$179,100	$579,500	$259,300	$426,100	$245,000	$234,300	$411,500
Occupied Housing Units	87.8	90.9	91.2	92.4	90.7	94	83.3	90.6	91.3	87.7	93.8
Owner-Occupied	63.8	63.1	64.4	59.6	60.4	48.6	59.4	51.8	67.3	62.4	63.5
1-Unit Detached Houses	61.6	66.9	52.5	63.6	62.7	49.3	41.8	36.8	44.3	65.4	46.3
Demographic											
Median Age	37.9	36.2	37.2	34.7	34.2	36.6	40.8	38.5	38.7	36.4	36.8
Bachelor's Degree or Above	31.5	37.8	37.4	34.4	32.4	33.7	31.5	39.4	37	30.8	50.6
Median Family Income	$60,293	$64,766	$68,715	$66,982	$65,381	$69,138	$54,239	$75,086	$69,465	$60,996	$100,732
Median Personal Income	$47,527	$48,781	$53,453	$48,840	$49,576	$47,626	$40,360	$57,871	$54,970	$45,119	$67,982
Real Estate Agent Market											
Median Wage	$23.53	$23.30	$14.63	$34.32	$32.96	$29.40	$22.44	$39.26	$21.58	$18.73	$23.48
Mean Wage	$29.83	$27.10	$20.23	$38.22	$37.77	$35.05	$32.03	$49.86	$28.99	$25.50	$30.88
Annual Median Wage	$62,060	$56,360	$42,090	$79,490	$78,560	$72,910	$66,610	$103,700	$60,300	$53,030	$64,230
Employment Per 1,000 Jobs	1.105	2.527	0.788	1.422	1.627	0.513	2.432	0.585	1.135	1.51	2.058

Notes: This table compares the Atlanta metropolitan area with the other top nine metropolitan areas in the U.S. as well as the whole nation from three perspectives: housing market, demographics, and real estate agent market. Housing market and demographic data is from the Census Bureau in the year 2018. Real estate agent market data is from Occupational Employment Statistics (OES) in the year 2019.

Table 2 Variable Selections for Financial Distress Prediction

Variable Name	Literature Support	Economic Meaning	Measurement
Total Commission Made by Agents	Corporate finance literature (Gombola et al., 1987; Jones and Hensher, 2004) document that operating cash flow (CFO) measures the ability of the firm to withstand adverse changes in operating conditions. Household finance literature (Fay, Hurst, and White , 2002; Gerardi et al., 2018) argues that household income is the key measurement of ability to repay debt.	We use commission fees earned by agents to measure the ability of real estate agents' to generate cash flow. We expect that real estate agents with higher revenue is are less likely to be financially distressed and file for personal bankruptcy when facing an economic hardship.	Measured by calculated commission based on transaction price and number of transactions
Commission Growth	Corporate finance literature (Rankov, and Kotlica, 2013; Kim, and Upneja, 2014.) argues that cash flow sustainability (measured by growth in operating cash flow) is also a crucial determinant of a firm's probability of going bankruptcy.	Commission growth measures the trend of potential for revenue growth of real estate agents. We expect that agents with a higher sale growth will perform better in the future and are less likely to be financially distressed.	Measured by change of the commission made by real estate agents over years
I(High Performance)	Whitaker (1999) and Platt and Platt (1991, 2002) emphasize the importance of adding industry-relative financial ratios (i.e., operating income relative to the industry) to improve the prediction of firms in financial distress.	The relative ranking of earnings values the ability of revenue-generating ability within a firm, which is relevant to the ability to earn expected future income.	Measured by whether or not the agent outperforms peers within the same firm. So, it is a relative ranking of earnings.
Working Experience	Waller and Jubran (2012) and Gilbukh and Goldsmith-Pinkham (2019) argue that agent experience is a critical factor for prediction of transaction outcomes and agents' performance.	Working experience can be used for prediction of future cash flow. More experienced real estate agents are likely to have a greater breadth of knowledge as to the local housing market and neighborhoods, and have developed ancillary relationships with appraisers, mortgage brokers, and others who may participate in the transaction process. On the other hand, Rookie real estate agents do not have enough social capital and experience and are more likely to exit the market. We add experience as one of the variables to predict the likelihood of bankruptcy and more experienced agents are less likely to fail and be financially distressed compared with rookie agents.	Measured by years since they got their real estate license.

Continued...

Variable Name	Literature Support	Economic Meaning	Measurement
Market Conditions	Barwick and Pathak (2015) and Gilbukh and Goldsmith-Pinkham (2019) mention that the market cycle could affect the outcomes of real estate agents since market condition affects whether a property gets sold and further affects the agents' performance.	The commission made by real estate agents is largely based on how well the whole real estate market is, and therefore, market condition is highly related to the earnings of real estate agents. We could expect that booming market conditions make real estate agents less likely to enter financial distress but bust market conditions increase the likelihood of financial distress of real estate agents.	Measured by average house price index changes in the region where agents' represented houses are located.
Firm Size	Turnbull and Dombrow (2007) and Chinloy and Winkler (2012) document that the size of firms where agents are working has a significant impact on their performance.	A real estate agent working in a big firm can easily get access to the resources and social capital provided by firms. Real estate agents may benefit from local brand recognition by buyers or sellers. Therefore, from the social capital perspective (Agarwal, Chomsisengphet and Liu, 2011), we believe that the size of the firm where they work can predict the performance of a real estate agent, and one who works in a big firm is less likely to be financially distressed.	Measured by total commissions made by that firm.
Disciplinary Record	Past misconduct negatively affects labor outcomes. For example, corporate finance literature finds that directors lose board seats when firms are involved in misconduct (Helland, 2006; Fich and Shivdasani, 2007) and the CEO suffers a reputational penalty following regulatory enforcement actions (Karpoff, Lee, and Martin, 2008). Besides, financial advisors with misconduct are more likely to move to substantially less popular firms both in monetary terms and in compensating differentials following misconduct, as documented by Egan, Matvos and Seru (2019). Another strand of literature documents the value of reputations in professional work. For example, Tadelis (2002) finds that individuals have incentives to maintain their reputation since they can sell their business toward the end of their career and the value of the business depends on their reputation. Schneider (2012) documents that reputation concern mitigates the asymmetric information between mechanics and motorists. Shi and Tapia (2016) argue that the reputation mechanism disciplines agent performance and potentially increases efficiencies in transactions with the agent, i.e., it induces agents to provide better service to their seller clients.	Real estate agents with a disciplinary record or who work in a firm which ever had a disciplinary record suffered from reputation damage and easily receive a negative feedback from clients, which further destroys their personal motivation and productivity. Also, agents with a disciplinary record are less likely to care about their reputation when making financial decisions, which plays a great role in the determinants of personal financial distress (Athreya, 2004; Cohen-Cole and Duygan-Bump, 2008). Therefore, we expect that real estate agents with a historical disciplinary record are more likely to perform worse and be financially distressed.	Measured by whether an agent or firm had a disciplinary record in the past.

Notes: This table gives the summary for the variables selection used for financial distress prediction. It lists the variable name, literature support, economic meaning as well as the measurement.

Table 3 Summary Statistics and Correlation Matrix of Variables

Panel A: Summary Statistics of Variables for Financial Distress Prediction

VarName	Obs	Mean	SD	P1	P25	Median	P75	P99
Agent Commission	181192	78113.44	83562.44	11040	13410	51120	1.15E+05	3.46E+05
Agent Commission Growth	181192	0.162	4.876	-11.748	-0.679	0	0.607	11.741
I(High Performance)	181192	0.354	0.478	0	0	0	1	1
Experience	181192	10.949	8.667	1	4	9	16	30
Firm Size	181192	6.92E+06	9.77E+06	7.11E+04	9.11E+05	3.45E+06	8.33E+06	4.49E+07
Avg Change in HPI	181192	0.02	0.08	-0.242	0	0.037	0.063	0.175
Agent Disciplinary	181192	0.028	0.165	0	0	0	0	1
Firm Disciplinary	181192	0.051	0.221	0	0	0	0	1

Panel B: Correlation Matrix of Variables

Variables	1	2	3	4	5	6	7	8
Agent Commission	1							
Agent Commission Growth	0.227***	1						
I(High Performance)	0.686***	0.141***	1					
Experience	0.068***	0.003	0.009***	1				
Firm Size	0.154***	0.025***	0.035***	0.015***	1			
Avg Change in HPI	0.187***	0.061***	0.042***	0.061***	0.168***	1		
Agent Disciplinary	-0.015***	-0.002	0.006***	0.103***	-0.033***	-0.010***	1	
Firm Disciplinary	-0.020***	-0.013***	0.004*	0.013***	-0.042***	-0.018***	0.115***	1

Notes:This table gives the summary statistics as well as correlation matrix for the variables used for financial distress prediction. Agent Commission is measured by calculating commission based on the transaction price and the number of transactions, and we use it to measure the ability of real estate agents to generate cash flow. Agent Commission Growth is measured by the change in the commissions made by real estate agents over years, and we use it to measure the trend and potential that the real estate agents have to grow. I(High Performance) is a dummy variable measured by whether or not the agent outperforms peers within the same firm, and we use it to measure agents' revenue-generating ability within a firm. Experience is measured by years since they got a real estate license, and we use it to predict agents' transaction outcomes and performance. Firm Size is measured by total commissions made by that firm, and we use it to measure the resources and social capital provided by firms. Avg Change in HPI is measured by average house price index changes in the region where agents' represented houses are located, and we use it to measure how well the whole real estate market is. Agent Disciplinary and Firm Disciplinary are dummy variables measured by whether an agent or firm had a disciplinary record in the past, and we use them to measure how the reputation concerns discipline the behavior of agents.

Table 4 Regression for Financial Distress Prediction

Panel A: Prediction of Financial Distress

	(1) BKR	(2) BKR	(3) BKR	(4) BKR	(5) BKR	(6) BKR	(7) BKR	(8) BKR
Agent Commission	-0.024***							-0.013***
	(-11.15)							(-5.75)
Agent Commission Growth		-0.003*						
		(-1.49)						
I(High Performance)			-0.101***					
			(-4.31)					
Experience				-0.008***				-0.006***
				(-5.60)				(-4.19)
Firm Size					-0.029***			-0.014**
					(-4.73)			(-2.23)
Ave Change in HPI						-2.197***		-1.101***
						(-20.93)		(-12.66)
Agent Disciplinary							0.096*	0.146*
							(1.67)	(1.89)
Firm Disciplinary							-0.051	-0.845
							(-1.04)	(-0.89)
N	181192	181192	181192	181192	181192	181192	181192	181192
Pseudo R^2	0.0431	0.0347	0.0351	0.037	0.0362	0.0628	0.034	0.124

Panel B: Univariate Analysis

Distress Ranking	OBS	Predicted Value	Ratio(1)	Actual Value	Ratio(2)	Listing Price	Act/Pre LP	Selling Price	Act/Pre SP
1	36238	187.5024	0.52%	186	0.51%	280558	1.08	254845	1.04
2	36238	220.5961	0.61%	208	0.57%	269688	1.05	245255	1.02
3	36240	248.6013	0.69%	254	0.70%	247345	0.98	212874	0.99
4	36238	313.2692	0.86%	292	0.81%	235187	0.97	205187	0.94
5	36238	622.0240	1.72%	635	1.75%	222905	0.91	192905	0.89

Distress Ranking	OBS	TOM	Pro (Sale)	Property Age	#Beds	#Bath	House Size(Sqft)
1	36238	110	0.59	22	4	2	2231
2	36238	108	0.60	22	4	2	2108
3	36240	104	0.58	19	4	2	2059
4	36238	99	0.58	21	4	2	2079
5	36238	96	0.61	21	4	2	2104

Notes: Table A reports the probit regression results for distress prediction and Table B reports the results for univariate analysis over the quintile of distress score.

Table 5 Impact of Financial Distress on Listing Price

Dep.Var	log(Listing Price)			
	(1)	(2)	(3)	(4)
$\widehat{Distress\ Score}_{i,t}$	**-0.048*** **	**-0.044*** **	**-0.042*** **	**-0.039*** **
	(-2.38)	(-2.73)	(-2.52)	(-2.79)
Baths	0.113***	0.104***	0.103***	0.108***
	(28.41)	(27.94)	(28.34)	(27.99)
Beds	0.001	0.001	0.001	0.002
	(0.18)	(0.11)	(0.12)	(0.14)
Age	-0.009***	-0.011***	-0.009***	-0.014***
	(-79.39)	(-93.85)	(-79.42)	(-93.82)
Age^2	9.12E-4***	9.20E-4***	9.11E-4***	9.18E-4***
	(59.77)	(67.06)	(59.69)	(67.01)
Log(House Size)	0.699***	0.679***	0.644***	0.687***
	(174.15)	(175.11)	(173.97)	(171.24)
Log(Lot Size)	0.093***	0.109***	0.081***	0.124***
	(111.62)	(129.08)	(111.83)	(142.09)
Individual FE	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes
CntyxYear FE	No	Yes	No	Yes
YQ FE	No	No	Yes	Yes
N	748,063	747,811	748,063	747,811
R^2	0.756	0.771	0.757	0.789

Notes: This table shows the regression results of the impact of financial distress on real estate productivity. The dependent variable is log(Listing Price). The independent variable we are interested in is Distress Score. Column (1) gives our result with individual fixed effects and Agent ZIPxYear fixed effects. Column (2) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and MarketxYear fixed effects. Column (3) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and Year-Quarter fixed effects. Column (4) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, MarketxYear fixed effects, and Year-Quarter fixed effects. Agent ZIP is the location where the real estate agents live. Market is the location of the agents' represented houses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Table 6 Impact of Financial Distress on Sale Price

Dep.Var	log(Sale Price)			
	(1)	(2)	(3)	(4)
$\widehat{Distress\ Score}_{i,t}$	**-0.049*** **	**-0.041*** **	**-0.044*** **	**-0.040*** **
	(-19.57)	(-19.42)	(-19.67)	(-16.84)
Baths	0.109***	0.104***	0.101***	0.115***
	(19.97)	(19.41)	(18.45)	(20.48)
Beds	0.013***	0.013***	0.013***	0.010***
	(4.74)	(3.44)	(4.75)	(3.94)
Age	-0.010***	-0.011***	-0.010***	-0.012***
	(-62.56)	(-63.45)	(-62.95)	(-72.51)
Age^2	9.22E-4***	9.11E-4***	9.01E-4***	9.20E-4***
	(39.47)	(41.57)	(39.52)	(45.35)
Log(House Size)	0.630***	0.641***	0.628***	0.606***
	(83.47)	(81.52)	(83.35)	(81.74)
Log(Lot Size)	0.050***	0.048***	0.039***	0.062***
	(47.07)	(48.41)	(46.77)	(54.26)
Individual FE	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes
CntyxYear FE	No	Yes	No	Yes
YQ FE	No	No	Yes	Yes
N	425,777	425,524	425,777	425,524
R^2	0.732	0.742	0.737	0.753

Notes: This table shows the regression results of the impact of financial distress on real estate productivity. The dependent variable is log(Sale Price). The independent variable we are interested in is Distress Score. Column (1) gives our result with individual fixed effects and Agent ZIPxYear fixed effects. Column (2) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and MarketxYear fixed effects. Column (3) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and Year-Quarter fixed effects. Column (4) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, MarketxYear fixed effects, and Year-Quarter fixed effects. Agent ZIP is the location where the real estate agents live. Market is the location of the agents' represented houses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Table 7 Impact of Financial Distress on TOM

Dep.Var	log(TOM)			
	(1)	(2)	(3)	(4)
$\widehat{Distress\ Score}_{i,t}$	**-0.132*** **	**-0.148*** **	**-0.138*** **	**-0.136*** **
	(-6.47)	(-6.70)	(-6.54)	(-7.20)
Baths	0.013***	0.011***	0.012***	0.014***
	(11.69)	(11.11)	(11.50)	(11.44)
Beds	0.006	0.007	0.004	0.005
	(0.91)	(0.87)	(0.96)	(0.89)
Age	-0.003***	-0.004***	-0.003***	-0.005***
	(-25.09)	(-21.43)	(-24.91)	(-22.90)
Age^2	0.001***	0.001***	0.001***	0.001***
	(25.58)	(24.76)	(25.39)	(23.45)
Log(House Size)	0.044***	0.043***	0.049***	0.047***
	(19.88)	(17.24)	(19.42)	(21.31)
Log(Lot Size)	0.027***	0.021***	0.028***	0.024***
	(33.01)	(23.04)	(33.08)	(28.86)
Individual FE	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes
CntyxYear FE	No	Yes	No	Yes
YQ FE	No	No	Yes	Yes
N	425,777	425,524	425,777	425,524
R^2	0.317	0.319	0.318	0.324

Notes: This table shows the regression results of the impact of financial distress on real estate productivity. The dependent variable is log(Time on Market). The independent variable we are interested in is Distress Score. Column (1) gives our result with individual fixed effects and Agent ZIPxYear fixed effects. Column (2) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and MarketxYear fixed effects. Column (3) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, and Year-Quarter fixed effects. Column (4) gives a result with individual fixed effects, Agent ZIPxYear fixed effects, MarketxYear fixed effects, and Year-Quarter fixed effects. Agent ZIP is the location where the real estate agents live. Market is the location of agents' represented houses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Table 8 Impact of Financial Distress on Other Outcomes

Dep.Var	Prob(Sale)	#Listing	#Sales	#Sales/#Listing
	(1)	(2)	(3)	(4)
$\widehat{Distress\ Score}_{i,t}$	0.029	-0.057	-0.275	-0.095
	(0.14)	(-0.41)	(-0.08)	(-0.28)
Individual FE	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes
CntyxYear FE	Yes	No	No	No
YQ FE	Yes	No	No	No
N	748063	208918	208918	208918
R^2	0.414	0.435	0.409	0.515

Notes: This table shows the regression results of the impact of financial distress on real estate productivity. The dependent variable is Prob(Sale) in Column (1), number of listings in Column (2), number of sales in Column (3), and ratio of sales to listings in Column (4). The independent variable we are interested in is Distress Score. All results add individual fixed effects, Agent ZIPxYear fixed effects, MarketxYear fixed effects, and Year-Quarter fixed effects. Agent ZIP is the location where the real estate agents live. Market is the location of agents' represented houses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Table 9 Robustness Test of Impact of Financial Distress

Panel A: Matched Sample Based on Brokerage Firm and Specialized Market

	By Brokerage Firm			By Specialized Market		
Dep.Var	Log(Listing Price)	Log(Sale Price)	Log(TOM)	Log(Listing Price)	Log(Sale Price)	Log(TOM)
$\widehat{Distress\ Score}_{i,t}$	-0.047***	-0.046**	-0.144***	-0.043***	-0.063***	-0.122***
	(-3.36)	(-2.51)	(-4.36)	(-6.74)	(-3.15)	(-4.59)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes	Yes	Yes
CntyxYear FE	Yes	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
N	132,450	79,136	79,136	191,262	109,283	109,283
R^2	0.778	0.764	0.375	0.776	0.763	0.359

Panel B: Matched Sample Based on Listing Market, Listing Time and Listing Price

	By Market x Listing Year			MarketxListing Year & Price	
Dep.Var	Log(Listing Price)	Log(Sale Price)	Log(TOM)	Log(Sale Price)	Log(TOM)
$\widehat{Distress\ Score}_{i,t}$	-0.039***	-0.031***	-0.102***	-0.021***	-0.117**
	(-4.31)	(-5.07)	(-4.14)	(-3.29s)	(-2.03)
Individual FE	Yes	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes	Yes
CntyxYear FE	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes
N	159086	93770	93770	42183	42183
R^2	0.779	0.766	0.364	0.745	0.462

Panel C: Subsample Test Based on the Transaction Period

	Boom(2000-2007)			Bust(2008-2011)			Recovery(2012-2020)		
Dep.Var	Log(Listing Price)	Log(Sale Price)	Log(TOM)	Log(Listing Price)	Log(Sale Price)	Log(TOM)	Log(Listing Price)	Log(Sale Price)	Log(TOM)
$Distress\ Score_{i,t}$	-0.034***	-0.032***	-0.131***	-0.093**	-0.062***	-0.189**	-0.049***	-0.044***	-0.167***
	(-4.74)	(-14.49)	(-2.68)	(-2.18)	(-5.97)	(-2.48)	(-6.63)	(-9.20)	(-2.97)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agent ZIPxYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MarketxYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	212474	118459	212453	166700	52326	166696	363755	249353	363751
R^2	0.800	0.763	0.398	0.781	0.746	0.302	0.778	0.763	0.363

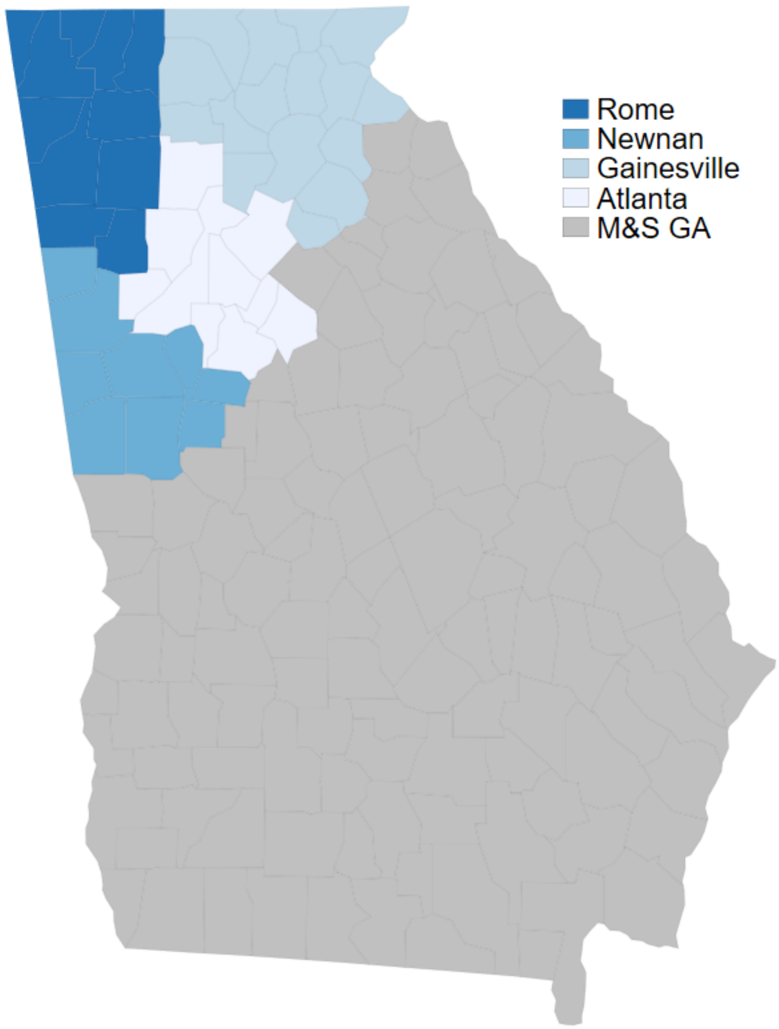
Notes: Panel A and B shows the regression results of the impact of financial distress on real estate productivity based on matched sample at agents' level and property's level. Panel C shows the regression results in three different sample periods. The dependent variables are log(Listing Price), log(Sale Price), and log(TOM). The independent variable we are interested in is Distress Score. All results add individual fixed effects, Agent ZIPxYear fixed effects, MarketxYear fixed effects, and Year-Quarter fixed effects. Agent ZIP is the location where the real estate agents live. Market is the location of the agents' represented houses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Table 10 Spillover Effect Test

	If (Loan)	Log(Loan Amount)	Log(Purchase Price)	LTV	Log(House Size)	Log(Lot Size)
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Distress\ Score}_{i,t-1}$	0.114***	0.042***	-0.01*	0.047**	-0.021*	-0.032*
	(3.51)	(4.33)	(-2.45)	(5.76)	(-1.83)	(-1.74)
Housing Attribute	Yes	Yes	Yes	Yes	Yes	Yes
CntyxYear FE	Yes	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,344	10,344	10,344	10,344	10,344	10,344
R^2	0.611	0.545	0.754	0.316	0.124	0.311

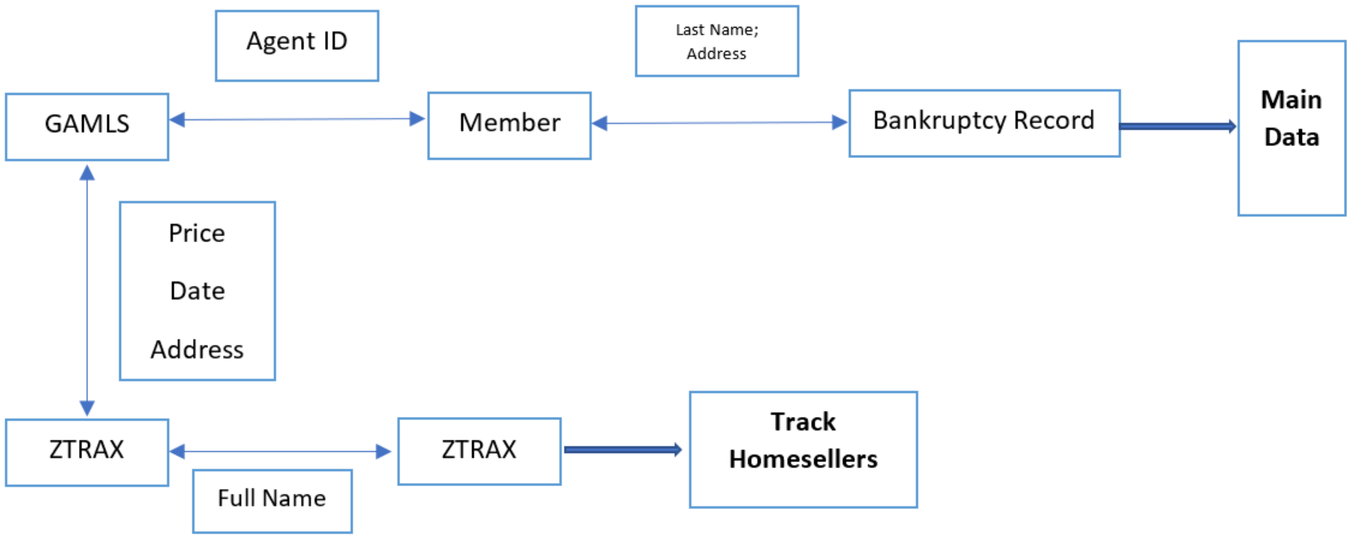
Notes: This table shows the spillover effect test. The independent variable we are interested in is Distress Score. All results add MarketxYear fixed effects and Year-Quarter fixed effects. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Standard error is clustered at the individual and year level.

Figure 1. Northern District of Georgia



Notes: This figure shows the areas of cities in Northern District of Georgia (NDGA). The district includes four cities: Atlanta, Rome, Newman, and Gainesville. The gray area denotes the middle and southern districts of Georgia. We only have access to fee-exemption data for NDGA.

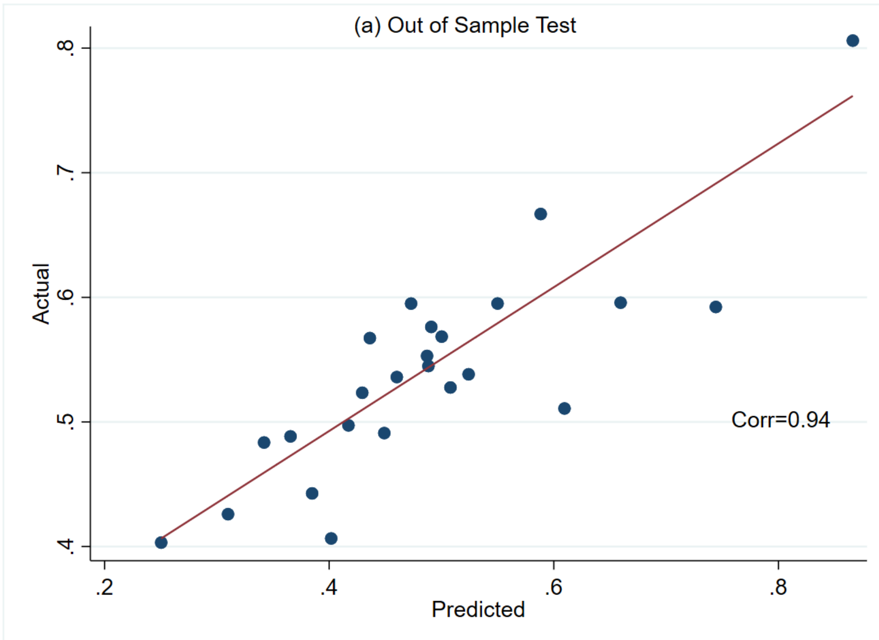
Figure 2. The Linkage among Three Datasets



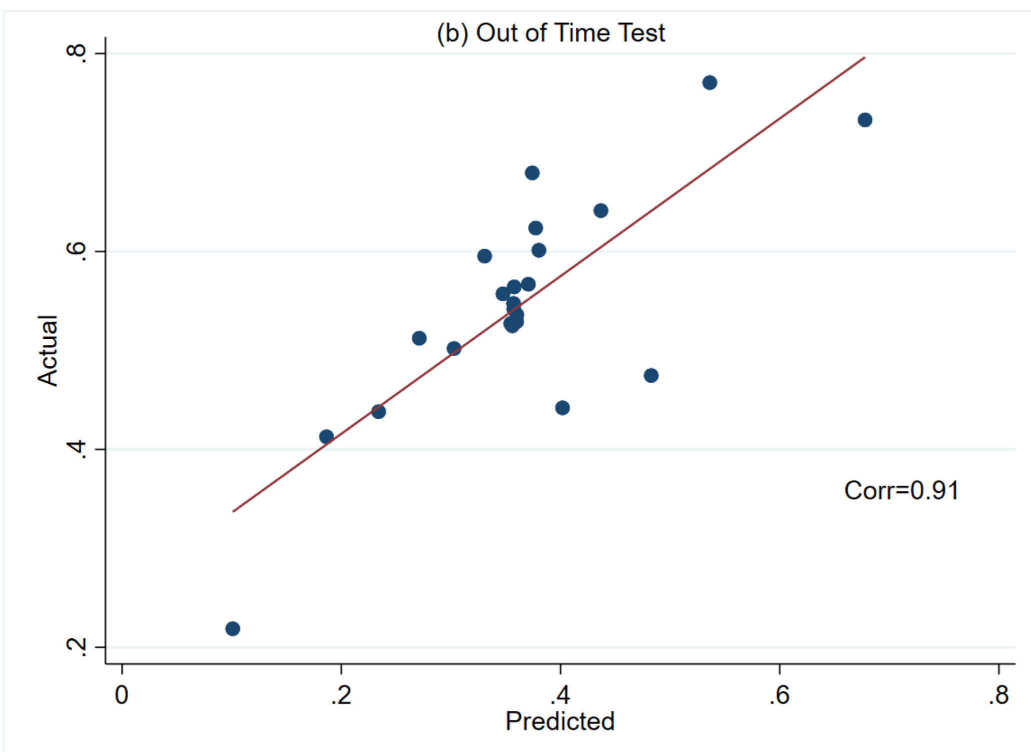
Notes: The figure shows the data linkage among three datasets. We merge the GAMLS listing data to bankruptcy files by taking advantage of Member data. We call it the GAMLS-member-bankruptcy merged data, which is used for our main regression. We describe how we merge the GAMLS listing data to the transaction data from ZTRAX based on sale price, sold date, and address of the property. The matched dataset is called GAMLS-ZTRAX data, which is used for identifying which home sellers' houses are represented by financially distressed brokers. We match seller name and buyer name within Zillow data to track the purchase activity and behavior of home sellers following Buchak et al. (2020).

Figure 3. Validation of Distress Prediction Model

(a) Random Sample

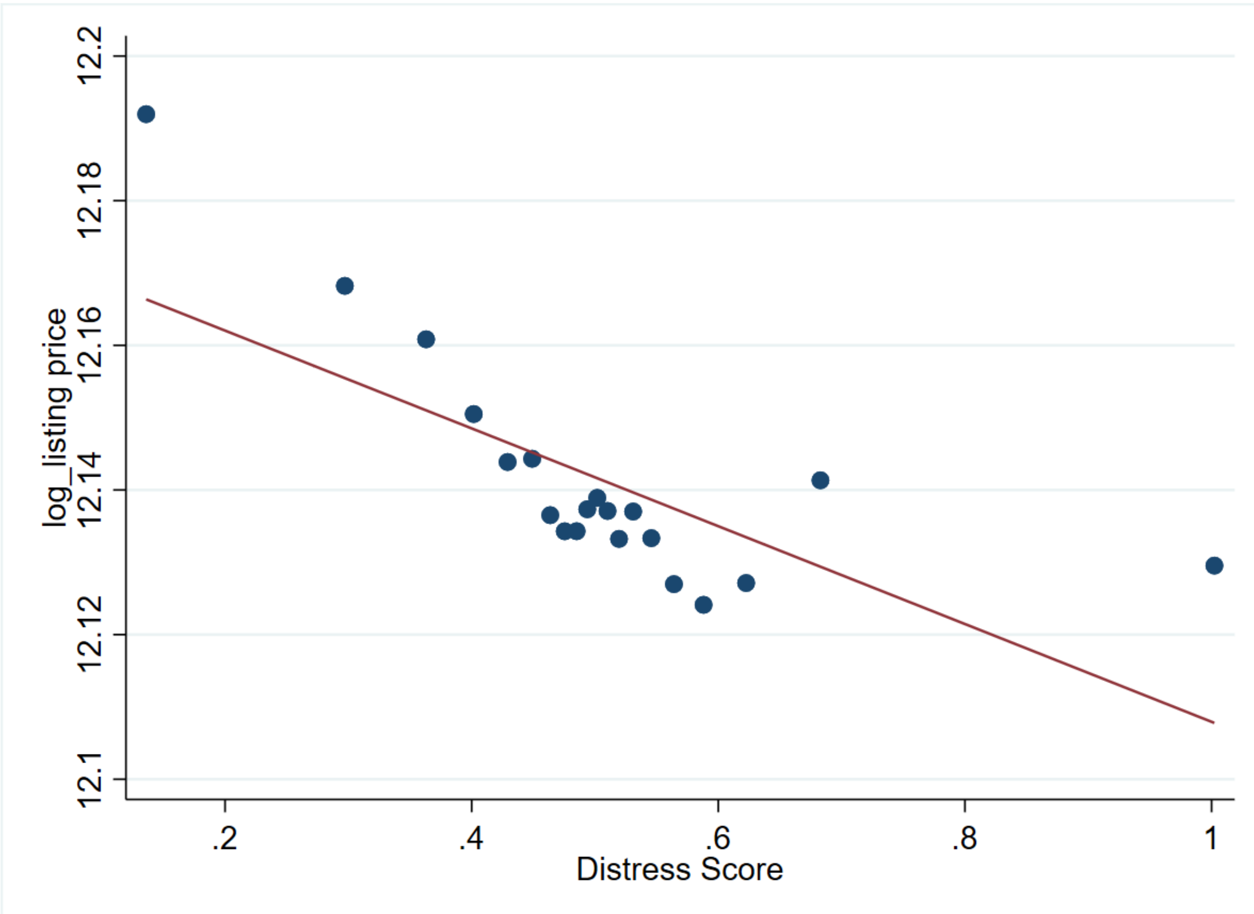


(b) Out of Time



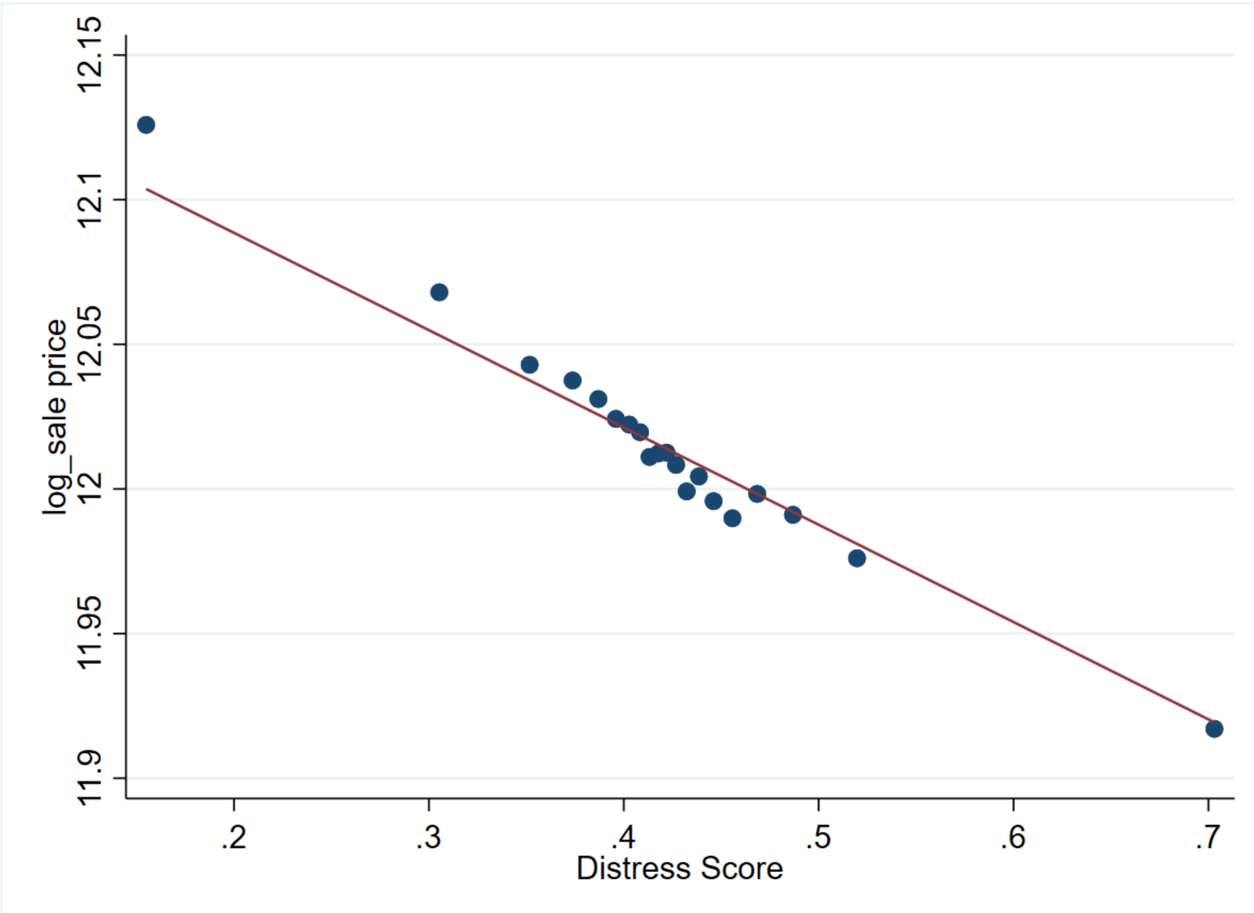
Notes: This graph shows the binscatter graph between predicted likelihood of bankruptcy filings and actual bankruptcy filings. Binscatter first regressed the actual bankruptcy filings and likelihood of bankruptcy filings on the agents fixed effects and year fixed effects, and generated the residuals from those regressions. Then binscatter plotted the best linear fit line constructed from an OLS regression of the y-residuals on the x-residuals.

Figure 4. Financial Distress Score and Listing Price



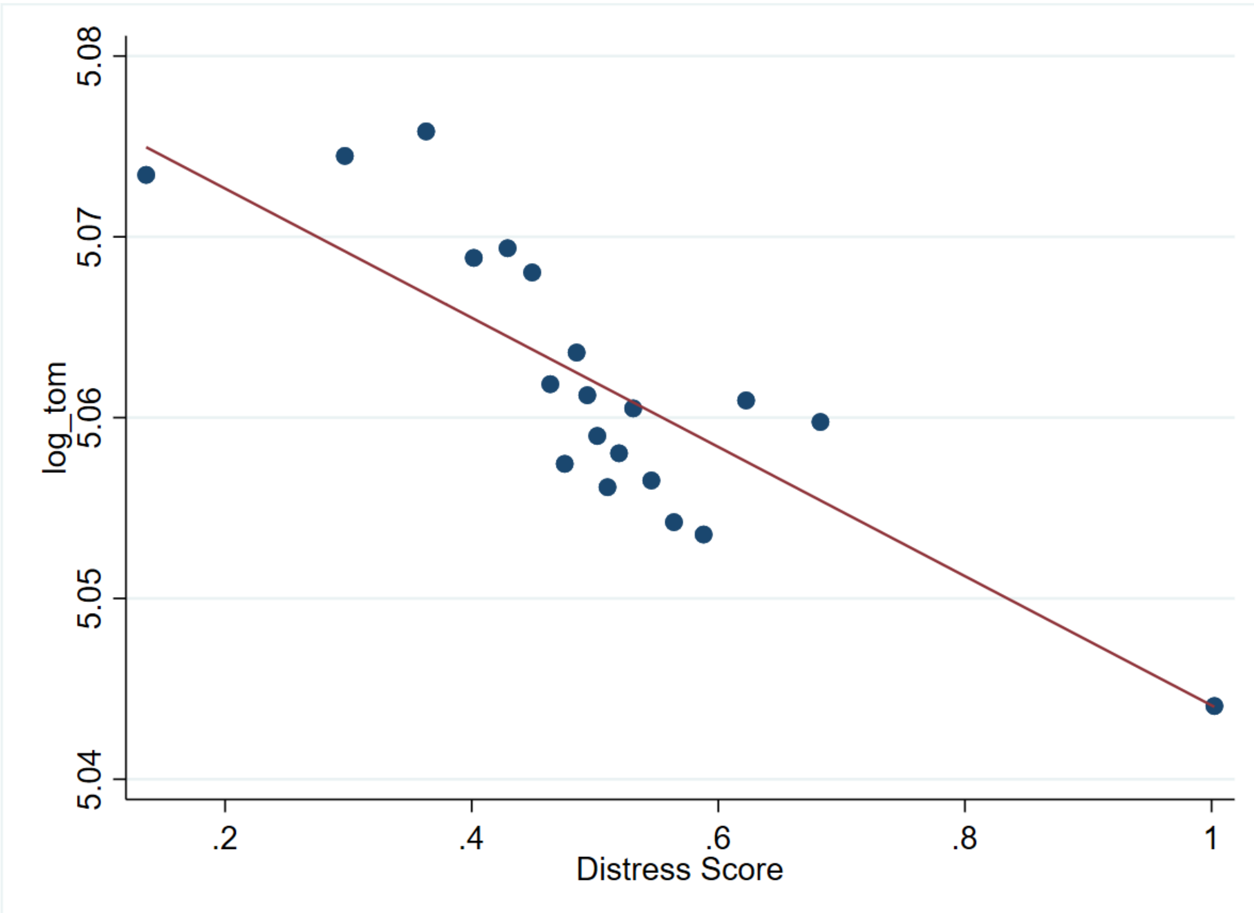
Notes: This graph shows the binscatter graph between predicted likelihood of financial distress and log(Listing Price).

Figure 5. Financial Distress Score and Sale Price



Notes: This graph shows the binscatter graph between predicted likelihood of financial distress and log(Sale Price).

Figure 6. Financial Distress Score and TOM



Notes: This graph shows the binscatter graph between predicted likelihood of financial distress and log(TOM).