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Flooding and Liquidity on the Bayou: The Capitalization of Flood Risk into House Value and Ease-of-Sale

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Abstract. The existing literature focuses on how perceived flood risk affects house value. Search theory, however, implies that flood risks will be capitalized into both house price and liquidity. This paper draws on search theory to develop an empirical approach for estimating flood risk capitalization into both price and selling time. The results show the mix of price and liquidity capitalization varies by level of flood risk as well as across housing market phases. Regardless of the specific capitalization pattern, the results illustrate that focusing solely on price without allowing for concomitant liquidity capitalization can yield estimates that understate the full impact of flood risk on house transactions.

JEL Codes: Q51, R21, R31

Keywords: Flooding, flood risk, amenity, house value, liquidity

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1. Introduction

All real estate is subject to the risk of some type of natural disaster--tornado, flooding, earthquake, etc.—the consequences of which range from modest inconvenience associated with completing minor repairs to outright devastation. Flooding, however, is of particular import in housing markets. Unlike many other natural disasters, the risk of flooding can be measured. And flood risk typically varies systematically across locations within a single urban area. Nonetheless, flood risk cannot be entirely fully insured; monetary costs can be insured to varying degrees, but the value of time and emotional costs associated with recovery cannot. As a consequence, flood risk is a location specific factor that is expected to be reflected in property values.

This paper re-examines the capitalization of flood risk in housing markets. The existing literature to date focuses entirely on the extent to which flood risk is capitalized into house value. But housing markets are search markets in which selling price and liquidity are two dimensions of asset value that cannot be separated; as a consequence, flood risk can be capitalized into price or liquidity, or a combination of both. Taking this insight as a starting point, this paper develops an empirical framework that yields consistent and asymptotically efficient measures of the simultaneous capitalization of perceived flood risk into house selling price and liquidity. It applies the framework to examine related waterfront amenity and flood risk effects of flood-prone bayous on property values in Baton Rouge, Louisiana.

The theoretical literature is clear about how housing consumption uncertainty or housing cost risks, whether from natural hazards or other sources, affects property value. Repair costs, whether certain or uncertain, reduce housing demand in locations with greater flood risk (Frame 1998, Glascock et al. 1991, Scawthorn et al. 1982) as does housing consumption uncertainty induced by flood risk (Turnbull 1991, 1994) even when the effects of such risks can be mitigated or fully insured (Turnbull 1994, Frame 1998). Greater flood risk reduces house values under actuarially fair or incomplete insurance. Flood risk also reduces values even when insurance is heavily subsidized, as in the U.S. national flood insurance program, unless the subsidy is sufficiently excessive.

The empirical literature is also clear about the general effects of flood risk on property value but unsettled about how the market responds to specific flood events. Barnard (1978), Shilling et al. (1985), Skantz and Strickland (1987), Speyer and Ragas (1991), Harrison et al. (2001), Bin and Polasky (2004), and McKenzie and Levendix (2010) use house sales data to estimate the impact of flood zone location on housing prices. All find that flood zone location reduces price, as expected. Shilling et al. (1985) employ a dummy variable to capture the net effects of flood risk and cost of flood insurance. Speyer and Ragas (1991) note that using dummy variables to pick up flood zone effects in hedonic models may also pick up other location effects because Federal Emergency Management Agency (FEMA) flood zones are assigned to broad geographic areas. They use spline functions to capture the effects of non-flood zone variables with purely locational variation.

Barnard (1978) uses elevation as the key variable to measure flood risk to distinguish the possible degrees of variation in risk within flood zones that a simple zone designation ignores. The results show that higher elevations have higher property values, indicating that there may be some variation of flood risk and housing prices within the 100 year flood plain. McKenzie and Levendix (2010) use pre- and post-Hurricane Katrina data and similarly conclude that homes with higher elevation command a premium over lower elevation homes in New Orleans. Their results also indicate that Katrina increased the premium for higher elevation homes, suggesting a greater flood risk discount for frequent or recent events.

Other studies focus on different aspects of flood zone heterogeneity, particularly the extent to which differences in flooding frequency affects house values. The empirical evidence concerning whether flood events alter perceived risks is mixed. Skantz and Strickland (1987) show that flood zone home prices are lower relative to comparable houses outside the flood zones and also that the discount does not change after a flood event. Bialaszewski and Newsome (1990) argue that flood plains have different histories of flood events and homeowner attitudes may be more strongly affected by the realized flooding frequency rather than predicted values. Yet, they find that location within a flood zone has no significant price effect. On the other hand, Bin and Polasky (2004) use a dummy variable for the post-hurricane landfall time period to pick up price effects of changing homeowner risk perceptions. The estimates indicate that the hurricane changed risk perceptions of homeowners; it appears that recent flood events tend to increase the perceived risk and depress housing prices further.

Morgan (2007) examines whether a flood event adjusts the market downward. The empirical results show that houses located in a designated flood zone sell at a premium indicating that the benefits of living next to water outweigh the flood risk. In contrast with Bialaszewski and Newsome (1990) and Skantz and Strickland (1987), Morgan finds that a flood event does change homeowners' risk perceptions and mitigates some of the amenity value of living next to water.

Finally, Harrison et al. (2001) examine the price effects of changes in the national flood insurance program itself. They include in their hedonic price function a dummy variable for transactions after the National Flood Insurance Reform Act of 1994.[1] Their results show that the program changes increased the price discount associated with flood zone locations.

This paper addresses two aspects largely overlooked thus far in the theoretical and empirical literatures; separate amenity and flood hazard effects and incorporating liquidity capitalization into the analysis. With respect to the first aspect, Morgan (2007) recognizes that higher flood risk is sometimes associated with amenities; waterfront property has its own appeal, which increases value, while at the same time exposing the owner to flood risk. Nonetheless, Morgan is unable to separate the two possibly offsetting effects—waterfront amenity versus attendant flood risk. This study uses geocoding to identify houses next to Louisiana bayous and rivers with a history of flooding as well as houses across the street without the riverfront amenity but also affected by the same flood risk to control for separate amenity and flood risk effects.

With respect to the second issue—liquidity—the theoretical and empirical literatures to date focus solely on how flooding or other natural hazard risks impact property values. Yet, there is more than one margin along which capitalization occurs in search markets—capitalization in both value and liquidity (Krainer 2001). Even when sellers are unable or reluctant to absorb a lower selling price because of equity constraints or for other reasons, diminished buyer willingness-to-pay still may be reflected in longer time on the market or reduced liquidity (Turnbull and Zahirovic-Herbert 2010). What is unknown is the extent to which flood risks are capitalized into liquidity and how accounting for this additional capitalization dimension in the

[1] The act established fines for mortgage lenders failing to ensure the mandatory purchase of flood insurance on Special Flood Hazard Area properties, increased the coverage limits of flood insurance policies, provided supplemental coverage for increased cost of compliance, established the flood mitigation assistance grant program, codified the National Flood Insurance Program Community Rating System, and required FEMA to assess its flood hazard inventory at least every 5 years. The act became law September 23, 1994.

empirical methodology affects value capitalization estimates. This paper applies the Turnbull and Zahirovic-Herbert (2010) (TZH) search model to the flood hazard situation to show that the answer to this capitalization question depends upon how flood risk affects the market determined price-liquidity tradeoff. It also uses the model to derive a system estimation framework to estimate bayou amenity and flood risk capitalization effects on both value and liquidity in the Baton Rouge, Louisiana, market.

The empirical results show that flood risks are capitalized into both house price and liquidity. There is no evidence of a significant amenity value for properties fronting bayous and rivers relative to properties across the street. Further, the price-liquidity capitalization patterns vary across weak and strong phases of the housing market, with broad flood zone effects exhibiting more modest price capitalization in the weak market and greater price and liquidity capitalization in the strong market. The difference in capitalization patterns is more severe for localized flood risks; localized risks are fully capitalized into price in the weak market phase and liquidity in the strong market phase.

The discussion is organized as follows. Section 2 explains the TZH search model and how it applies to the price-liquidity flood risk capitalization process. Section 3 explains the implications of the TZH approach for empirically measuring price and liquidity effects using standard house transactions data. Sections 4 and 5 present and evaluate the empirical models and estimates. Section 6 concludes.

2. A Model of Search, Price and Liquidity

The TZH model is a stylized framework of house seller strategy in a search environment. This section summarizes the model and applies it to the problem of empirically sorting out the different channels through which riverfront amenity and flood risk affect house transactions; see Turnbull and Zahirovic-Hebert (2010) for additional details and derivations of general properties. The TZH approach generalizes what has become a standard seller search model in housing market analysis.[2] The model also offers a choice-theoretic framework that motivates the empirical approach taken in this study.

2.1 Seller Preferences

Consider the seller of a given house with characteristics summarized in the vector **x**, which includes variables describing property flood risk. The seller's holding cost per unit of time is *h*. Denoting the time it takes to sell the property by *T*, the seller's expected holding cost or cost of waiting for a sale to occur is $E[hT] = hE[T]$. The seller prefers a higher expected selling price, $E[P]$, and lower expected holding cost, $hE[T]$, ceteris paribus. Therefore, seller utility is given the quasiconcave utility function $U\left(E\left[P\right], hE\left[T\right]\right)$, with partial derivatives $U_1 > 0$ and $U_2 < 0$. Applying the implicit function theorem to the utility function for a given level of utility, the slope of an indifference curve in expected selling time-price space is

$$\left(\frac{dE\left[P\right]}{dE\left[T\right]}\right)_{dU=0} = -h\frac{U_1}{U_2} > 0 \qquad (1)$$

Figure 1 portrays the indifference curves in expected selling time (inverse liquidity) and expected price space that are generated by one seller's utility function. Indifference curves to the northwest indicate higher utility. The upward slope follows from the seller's preference for a

[2] See Haurin (1988) for a seminal application of a popular version of the search model to housing.

higher expected selling price and shorter expected selling time. The curvature reflects the rate of time preference, that is, how the seller's required tradeoff between expected price and expected selling time changes with greater expected selling time. Different sellers, of course, likely have different holding costs as well as different time preference rates, and so have different indifference curve maps in a diagram like figure 1. It is sufficient for our purposes to focus on one representative seller of a particular house, though, so we do not need to deal with that complication here. Finally, as in all mainstream search market models, it is worthwhile to note that the seller only cares about the selling price and liquidity, that is, the net return from the sale of the house. The house characteristics themselves (including flood risk or amenities) do not enter the seller's utility function at this point.

The utility function (and associated indifference curves) portrays the extent to which the seller is willing to tradeoff selling price and liquidity. The next question to consider is: what are the opportunities facing the seller under current market conditions?

2.2 The Market Price-Liquidity Constraint

The seller sets the reservation price, s, following the usual threshold rule: sell to a buyer offering b if $b \geq s$ and do not sell if $b < s$. The market distribution of buyers in terms of their offers for a house with characteristics $\mathbf{x}$ is $F(b,\mathbf{x})$. The probability of a buyer arriving during the interval dt is π. The probability that the arriving buyer's offer b will meet or exceed the seller's reservation price is $[1- F(s,\mathbf{x})]$. Therefore, the probability that the house will sell during dt is $\pi[1-F(s,\mathbf{x})]dt$. The house time on the market, T, is stochastic, and the expected time on the market is

$$E[T] = 1/\pi\left[1 - F(s,\mathbf{x})\right] \tag{2}$$

and the expected price of a house that sells is

$$E[P] = \int_{b \geq s} b\pi dF(b, \mathbf{x}) / (1-\pi) F(s, \mathbf{x}) \tag{3}$$

For a house with characteristics **x**, the selection of reservation price *s* determines both $E[T]$ and $E[P]$. Therefore, a consequence of viewing the housing market as a search market is that both expected selling price and liquidity (inverse of selling time) are determined by the same factors—property characteristics **x** and the seller reservation price *s*.[3] To summarize the relationships among these variables, note that equations (2) and (3) imply $dE[T]/ds > 0$ and $dE[P]/ds > 0$, so that (2) and (3) can be recast in price-selling time space as

$$\Phi(E[P], E[T], \mathbf{x}) = 0 \tag{4}$$

the upward-sloped curve in figure 1. This curve is the mapping of price and selling time from (2) and (3) when tracing the seller's reservation price over the entire support of *F* for given **x**. This curve can be interpreted as the market-determined expected price-liquidity constraint facing the seller. It delineates the only feasible combinations of expected selling price and expected selling time for the house with characteristics **x,** given the market conditions reflected by the buyers'

[3] The canonical seller search model assumes that the distribution of buyer types is stable over time, in which case the seller's optimal reservation price is unchanging as well. If the distribution of buyer types systematically changes over time, for example, each buyer's willingness-to-pay for given house characteristics change with the market exposure of a given house, then the seller's optimal reservation price can vary with longer realized time on the market. Nonetheless, it turns out that the empirical results are the same for both the constant and time-varying *s* cases, so the formal discussion focuses exclusively on the simpler framework. The time-varying *s* results are available in an optional appendix.

demands reflected in the arrival rate π and distribution function F. (The curve is not linear in general.) By construction, the constraint is a one-to-one mapping of s into $E[T]$-$E[P]$ space. Therefore, the seller chooses a particular point $\{E[T], E[P]\}$ on the constraint by setting the appropriate reservation price, s.

From (2) and (3) it can be shown that a greater buyer arrival rate decreases expected selling time and increases expected sales price for each given s, shifting the market constraint to the northwest to $\Phi' = 0$ as pictured in figure 2. (Point a on the original market-determined price-liquidity constraint corresponding to a particular seller reservation price s shifts to point a' on the new constraint.) A lower buyer arrival rate shifts the constraint to the southeast to $\Phi'' = 0$ in the figure. Changes in buyers' valuations of the given house similarly shift and rotate the price-liquidity constraint. Increasing a desired characteristic increases buyer valuation of the property, shifting the distribution F rightwards, which can be shown to decrease the expected selling time and increase the expected sales price for each given s. This shifts the market constraint northwest in figure 2, the same general effect as an increase in buyer arrival rate. Similarly, decreasing a desired characteristic of a house shifts the market constraint rightwards in figure 2, much like the effect of a decrease in buyer arrival rate.

The constraint (4) fully summarizes market conditions for the house. Stronger buyer demand for the given neighborhood is reflected in a greater arrival rate; weaker buyer demand for the given neighborhood is reflected in a lower arrival rate. A more desired characteristic in the given house increases buyers' demands for the house or laterally shifts the distribution of buyer bids F to the right. Less desirable characteristics decrease buyers' demands, laterally shifting the distribution of buyer bids F to the left. These results imply that the waterfront amenity shifts the price-liquidity constraint to the northwest; at the same time, being located in a flood zone shifts the price-liquidity constraint to the southeast. Figure 3 illustrates several possibilities. The price-liquidity constraint without flood risk or the waterfront amenity is given by $\Phi = 0$. The flood risk shifts the constraint southeast to $\Phi' = 0$. But an otherwise identical waterfront house subject to the same flood risk shifts the constraint to $\Phi'' = 0$ or possibly even to $\Phi''' = 0$ if the amenity effect is strong enough to over-shadow the flood risk effect.

2.3 Equilibrium Expected Price and Selling Time

To complete the model, the seller's problem is to set the reservation price *s* to maximize utility subject to (2) and (3). It turns out to be more useful to restate this problem as the equivalent problem of the seller choosing the expected price and holding cost to maximize utility subject to the market determined price-selling time constraint (4), or

$$\max_{E[P],E[T]} U\left(E[P], hE[T]\right) \text{ s.t. } \Phi\left(E[P], E[T], \mathbf{x}\right) = 0 \qquad (5)$$

Casting the problem this way makes it easier to establish the parallels between this search theory and neoclassical consumer demand theory, a connection key to understanding the empirical approach implied by the model. Intuitively, the seller sets reservation price *s** such that the resultant expected selling price and liquidity satisfy the tangency between the indifference curve *U** and the market constraint summarized in the market-determined price-liquidity trade-off $\Phi = 0$, as depicted by the outcome $\left\{E[T]^*, E[P]^*\right\}$ corresponding to point *a* in figure 1. The diagram establishes a key insight for the empirical model: this version of the problem is equivalent to the seller choosing the $\{E[T], E[P]\}$ combination solving the constrained maximization problem (5).

2.4 Amenity and Flood Risk Effects

Flood risk shifts the price-liquidity constraint (4) to the southeast from $\Phi = 0$ to $\Phi' = 0$ in figure 3. While the precise effects on the seller's strategy depend upon the shape of his indifference map, in general the flood risk shifts the seller's optimal strategy from point *a* on $\Phi = 0$ to a point like *b* on $\Phi' = 0$; expected selling price declines, expected selling time rises, or a combination of both. Greater capitalization of the flood risk into the selling price implies less capitalization into selling time or difficulty of sale. Similarly, greater capitalization into selling time implies less capitalization into selling price.

Adding the waterfront amenity effect shifts the price-liquidity constraint (4) from $\Phi' = 0$ to either $\Phi'' = 0$ or $\Phi''' = 0$, depending on the relative amenity value. As a result, the equilibrium shifts from point *b* to either *c* or *d*, respectively. Once again, the capitalization of the amenity value relative to flood risk property without the amenity will be evident in higher price, faster selling time, or both (compare expected price-selling time combinations at *c* or *d* relative to *b* in figure 3). The various possibilities for the observed net effect of a riverfront location relative to no flood risk are also easily seen from the figure.

3. Price-Liquidity Empirical Model

As illustrated by the model in the previous section, all search and matching models of the housing market are similar in that they model price and selling time as jointly determined outcomes so that different market or property characteristics typically lead to combined price and liquidity effects. At the least, this suggests that simultaneous selling time or liquidity effects be taken into account in the empirical analysis. This simultaneous determination of price and selling time in equilibrium, however, creates econometric difficulties. After all, as should be clear from the theory above, both price and liquidity are simultaneously determined by the same set of factors underlying seller utility and the market constraint. Econometrically, the equations describing price and liquidity are functions of the same set of variables and therefore appear to be an under-identified simultaneous system.

Various researchers have taken different approaches to dealing with the fact that price and selling time are determined simultaneously. Some of the earliest studies simply use a single regression equation to estimate selling time determinants (Belkin et al. 1976, Miller 1978, Kang and Gardner 1989, Asabere and Huffman 1993). Later studies try to implement simultaneous or two-stage models in order to account for selling price-selling time simultaneity (Sirmans et al. 1991, Yavas and Yang, 1995, Forgey et al. 1996, Huang and Palmquist 2001, Rutherford et al. 2001, Knight 2002, Turnbull and Dombrow 2006, Turnbull et al. 2006, Zahirovic-Herbert and Turnbull 2008). Studies in this second group use a variety of approaches to solving the identification problem, but most reduce to ad hoc exclusion conditions imposed by assuming that some property characteristics only affect selling price while others only affect selling time. Turnbull and Zahirovic-Herbert (2008) appeal to implied parametric restrictions across selling price and selling time equations to show that the identification problem can be solved without such ad hoc exclusion conditions. But their approach can be computationally difficult in large data sets.

In contrast to the preceding literature, in the TZH model the seller selects expected selling price and liquidity as a straightforward application of neoclassical consumer demand theory (in which $E[P]$ is a good and $E[T]$ a bad), maximizing utility subject to a feasibility constraint. Just as the utility maximization model in consumer theory yields the consumer's demands for two goods Y and Z as functions of the same predetermined variables (consumer preferences, prices of Y and Z, and income), the seller utility maximization model summarized above yields expected selling price and selling time both as functions of the same set of predetermined variables (seller preferences, property characteristics, and market conditions—the last of which also reflects buyers' preferences, etc.).

More formally, recall that the search model offered here implies that expected price, $E[P]$, and selling time or liquidity, $E[T]$, are co-determined by the two equilibrium conditions for utility maximization: the constraint $\Phi = 0$ and the tangency condition $-hU_2/U_1 = -\Phi_{E[T]}/\Phi_{E[P]}$. The implicit function theorem states that there exists a solution to these conditions that can be expressed as differentiable functions of the exogenous property attributes, market conditions, etc.,

$$E[P] = g_P(\mathbf{x}) \tag{6}$$

$$E[T] = g_T(\mathbf{x}) \tag{7}$$

Assuming a semi-log form for expected selling price and linear form for expected time on the market and adding the jointly distributed stochastic errors ε_p and ε_T, an empirical model of the realized selling price and time on the market therefore follows as

$$\ln P = \sum_i \alpha_i x_i + \varepsilon_p \tag{8}$$

$$T = \sum_i \beta_i x_i + \varepsilon_T \tag{9}$$

The mathematical structure of the underlying optimization problem parallels the consumer's problem in demand theory. Demand theory yields demand equations that are functions of the same predetermined variables and the constrained optimization model of price and selling time also yields equations (8) and (9) that are functions of the same set of exogenous variables in vector **x**. Finally, realized price and selling time are co-determined by the same factors at the same time, which in turn means that the error terms may be correlated across equations. Seemingly unrelated regression (SUR) is an appropriate technique for obtaining efficient estimates in the presence of such cross equation correlation. This is the same method for estimating a system of consumer demand equations.[4]

4. Data and Variables

This study uses the Multiple Listing Service (MLS) data for broker-assisted transactions completed between October, 1984, and April, 2005, in East Baton Rouge Parish, Louisiana (parishes in Louisiana are equivalent to counties in other states). The Baton Rouge metropolitan area has a population of about one half million during the sample period. The sample period ends three months before hurricane Katrina and so avoids the housing market distortions induced by the sudden influx of population in the aftermath of the historic devastation of nearby New Orleans. The sample period covers two decades during which the local housing market experienced a downturn driven by a long deep regional recession in the oil based economy,

[4] As a robustness check, we also use the Turnbull and Zahirovic-Herbert (2008) identification approach to estimate an alternative simultaneous selling price-marketing time formulation that allows for a marketing time-dependent seller reservation price. The resultant 2SLS estimates from that approach yield conclusions identical to those reported below. These results are available in an optional appendix.

followed by a modestly rising market. Therefore, the sample allows us to investigate the extent to which flood effects on price and liquidity vary over the market cycle.

The data cover detached single family houses transactions recorded in the Baton Rouge MLS. We apply several filters to systematically clean the data; none of the filters differ from those employed in other studies drawing from the same or similar data. We avoid the new subdivision pricing bias by excluding from our sample houses that are at less than four years old since the prices of houses in new subdivisions can diverge from the broader market until the new development reaches a critical mass (Sirmans et al. 1997). MLS listings were published in bi-weekly books during most of the sample period, which means that newly listed houses did not appear in print for up to 14 days. Therefore, in order to restrict the sample to houses with full market exposure, we exclude houses that sell in fewer than 14 days. The 997 houses on the market more than 400 days appear to be outliers, and so are also dropped from the sample. Since preliminary analysis reveals that this market exhibits segmentation, we eliminate houses that sell for less than $40,000 (3983 observations) or more than $320,000 (1355 observations) from the sample.[5] In order to minimize data errors, we also drop houses with unusually small or unusually large living area (less than 300 or greater than 4500 square feet) or unusual net area of utility rooms, covered porches, and carports (less than 110 and greater than 4000 square feet). The cleaned data set comprises 27,939 transactions.

Table 1 reports summary sample statistics for the variables. The sales price (*Price*), days on the market prior to sale (*DOM*), number of bedrooms (*Bedrooms*), number of bathrooms (*Bathrooms*), the age of the house (*Age*), living area (*Living area*), and the number of fireplaces (*Fireplaces*) are drawn directly from MLS sales records. The *Net area* variable is calculated as the difference between the total square footage under roof less the square footage of living area.

[5] The omitted market segments do not have sufficient numbers of observations for separate flood risk analysis.

Note that our measure of marketing time, *DOM*, measures the time on the market with the selling agent. Therefore, *DOM* understates the total market exposure for those houses with expired first listing and subsequent relisting with different brokers. Although a common problem with many MLS based data sets in the literature, the *DOM* estimates likely will be biased for houses that are relisted with different brokers after listing expiration; the direction or size of the bias for these houses is not known, not the least because it is not unusual for sellers to complete modest remodeling or repairs before relisting (Krainer 2001).

All of the models also include year and seasonal fixed effects. Location controls in all of the models include distance to the central business district, *Distance CBD*, distance to LSU, *Distance LSU*, and a complete set of census block dummy variables. This location fixed effects approach is similar to Clapp et al. (2008) who use census tract fixed effects to control for omitted neighborhood characteristics. In our case, fixed effects are based on census block groups that are a very small geographic measure of the neighborhood market; in some cases smaller than the geographic extent of single subdivisions in Baton Rouge. We use 265 fixed effects; the smallest census block group has only 36 observations and the largest 1,938 observations.

All of the models also include direct controls for housing market microstructure or neighborhood market conditions. The neighborhood market condition variables follow Turnbull and Dombrow (2006) and are constructed as follows. A competing house j in the neighborhood of the subject house has to be on the market at the same time, within one mile, and within 20% of the living area of the subject house i. Each overlapping listing j is weighted by the square of the inverse distance between the houses i and j to capture the notion that nearby houses have stronger competition effects than do houses that are farther away. Let $l(i)$ and $s(i)$ denote the listing date and sales date for house i. The days-on-market or selling time for house i is $s(i)$-$l(i)$+1 so that the overlapping time on the market for house *j* is $\min[s(i),s(j)]-\max[l(i),l(j)]+1$. The straight-line distance in miles between houses *i* and *j* is *D(i,j)*. The measured neighborhood competition for house *i* is therefore

$$Listing \quad density(i) = \sum \frac{(1-D(i,j))^2 \{\min[s(i),s(j)] - \max[l(i),l(j)]\}}{s(i)-l(i)+1}$$

where the distance weighting diminishes with greater distance between house *i* and each competing house *j*. We use the STATA algorithm provided by Zahirovic-Herbert (2010) to construct this variable using all applicable competing house sales, which include all relevant competing houses listed before and after the estimation period, January 1985 to March 2005, that overlap with the listing period for each house sold in the sample. Table 1 reveals that there are about 2.5 competing houses each day the average house is on the market, but this measure of neighborhood competition exhibits wide variation across houses in the sample, ranging from zero to over 20.

A competing listing in the neighborhood can either increase competition with the house in question or create a shopping externality by increasing the traffic of potential buyers to the neighborhood (Turnbull and Dombrow 2006). If the competition effect dominates then increasing surrounding listings will decrease selling price, lengthen time on the market, or both. If, on the other hand, the shopping externality effect dominates then increasing surrounding listings will increase selling price, shorten time on the market, or both. Neighborhood market condition variables are typically significant in price and selling time equation systems (Turnbull and Dombrow 2006, Turnbull et al. 2006, Turnbull and Zahirovic-Herbert 2010, 2011, Zahirovic-Herbert and Turnbull 2008).

We note at this point that neighborhood market conditions are often argued to be the source of spatial correlation. This suggests that including *Listing Density* in the empirical models ameliorates the usual argument for applying spatial correlation corrections (Turnbull and Zahirovic-Herbert 2011). Nonetheless, recall that all of our models include spatial fixed effects (265 census block groups). Clapp et al (2008) argue that such detailed fixed effects alone should be adequate to control for omitted neighborhood effects. In a different vein, Davis (2004) points out that estimating such a model with clustered errors provides a flexible approach to spatial econometrics (Davis 2004, Heintzelman 2010), an alternative to spatial lag models.[6]

The empirical models in this paper also include the variables *Larger* and *Smaller* to control for price and liquidity effects from a given house being either larger or smaller than the average house in the surrounding neighborhood (Turnbull et al. 2006). To construct the relevant variables, we index all houses within a one half mile radius of house *i* by *J*, and then calculate house size measured relative to the average living area in the surrounding neighborhood as

$$Size_i = \frac{Living\ \ area_i - \sum_{j \in J} Living\ \ area_j \big/ N_J}{\sum_{j \in J} Living\ \ area_j \,/\, N_J}$$

where N_J denotes the number of surrounding houses in the neighborhood *J*. Using this intermediate calculation, we define the variables $Larger_i$ and $Smaller_i$ as the absolute values of

[6] Nguyen-Houng and Yinger (2011) note that the popular special lag model does not necessarily mitigate omitted variable bias (Pace and LaSage 2010). In any case, to allow for an alternative source of spatial price effects, we also estimate models in which competing houses with overlapping listings are defined based on listing price rather than living area (the approach reported in this paper). Since list prices of overlapping listings are observed by both buyers and sellers, this alternative formulation may be interpreted as closer in spirit of the source of spatial price effects. The alternative formulation, however, yields the same conclusions as those reported in this paper. The results are available in an optional appendix.

the positive and negative values of $Size_i$ to allow for asymmetric relative house size effects on value:

$$Larger_i = |Size_i| \text{ for } Size_i > 0 \text{ or } = 0 \text{ otherwise;}$$

$$Smaller_i = |Size_i| \text{ for } Size_i < 0 \text{ or } = 0 \text{ otherwise.}$$

It is important to remember that these variables are not dummy variables when interpreting the coefficient estimates.

The *Vacant* dummy variable indicates an unoccupied property. When controls for spatial competition/shopping externalities and relative size are included in the model, the *Vacant* coefficient should primarily pick up the net effects of higher seller holding costs and lower seller bargaining power associated with vacant properties (Harding et al. 2003, Turnbull and Zahirovic-Herbert 2011).

The *Rental* dummy variable indicates a tenant occupied house. Previous studies tend to find rental houses selling at a discount, reflecting the rental externality as well as the legal and practical restrictions limiting the showing of tenant occupied houses.[7]

The main variables of interest relate to flood risk and waterfront amenity. All properties are categorized by their flood zone ranking, indicated by the dummy variables *Highest Risk Zone*, *Medium Risk Zone*, and the omitted category is the lowest risk zone. East Baton Rouge Parish contains five different flood zone categories. Several of the categories, however, have too few observations for meaningful analysis. Therefore, we partition the five categories into three zones that preserve their relative risk rankings. The *Highest Risk Zone* contains all houses in the two highest risk zones (areas with a 1% or greater annual chance of flooding, hence a 25% or

[7] See Turnbull and Zahirovic-Herbert (2011) for a summary of the relevant theoretical and empirical literatures.

greater chance of flooding over the life of a 30 mortgage), *Medium Risk Zone* contains all houses in the next two highest risk zones (areas with between 0.2% and 1% annual chance of flooding), and the omitted flood risk dummy variable category pertains to the lowest risk zone in the parish (areas with a 0.2% or less annual chance of flooding). While Louisiana has the greatest number of repetitive losses properties in the U.S., East Baton Rouge Parish exhibits the fifth highest repetitive and severe repetitive loss properties in the state. Approximately 40% of the total land area of the Parish falls into the 100 year flood frequency category. Most flooding is attributed to river and bayou backwater flooding.

Drawing from local press reports, we identify the various bayous and rivers in East Baton Rouge Parish that are active risk locations, with multiple localized flood events and one major event reported during the sample period.[8] The variables *Bayou* and *Near Bayou* are dummy variables for houses within 300 and 500 feet of the nearest bayou or river, respectively. Based on an examination of the mapped data points, the *Bayou* variable captures houses fronting water or with a direct water view while the *Near Bayou* variable includes houses across the street from *Bayou* houses. Therefore, by construction the variable *Near Bayou* includes houses without direct water views but near enough to the water to be affected by the same periodic localized flooding affecting *Bayou* houses. (The topography is extremely flat so that houses with other houses between them and the river or bayou have, at best, obstructed water views.) The coefficients on the flood zone variables pick up the value and liquidity effects of being in a broad flood zone, much like the existing flood risk capitalization studies discussed earlier. The *Near*

[8] The principle flooding in the parish is caused by backwater flooding along the Amite and Comite Rivers and their tributaries. Besides the flooding caused by the Amite River, the major tributaries that are affected by backwater include: the Comite River, Jones Creek, Claycut Bayou and Bayou Manchac. The backwater of Bayou Manchac in turn affects Ward Creek and Bayou Fountain. The backwater that affects the Comite River also causes major flooding to its tributaries which are Draughan Creek, Beaver Bayou, Shoe Creek, Blackwater Bayou, Hurricane Creek and lower Cypress Bayou. The major floods causing the most damage on the Amite River, Comite River and their tributaries occurred in 1953, 1977, 1979, 1980, 1983 and 1990. These floods range in severity from 10 to 50 year floods.

Bayou coefficients in the hedonic price and selling time equations pick up value and liquidity effects of regular or recent flood events, over and above the high risk zone effects. The *Bayou* coefficients therefore pick up any additional value or selling time effects from the water frontage or view amenity.

Of the total sample of 27,939 transactions in our sample, 6,754 are for houses in the *Highest Risk Zone*, 6,671 are for houses in the *Medium Risk Zone*, and the rest are for houses in the lowest risk zone. The sample includes 1,679 *Bayou* and 3,228 *Near Bayou* transactions (recall that all *Bayou* houses are also *Near Bayou* houses).

5. Empirical Results

Table 2 reports the price and selling time equation SUR estimates for the full sample. The first two columns report base model results, without flood zone variables. The second set of estimates introduces flood zone variables and the third set also includes the variables controlling for proximity to bayous and rivers that experience flooding. The last set of results in the table report bootstrapped standard errors. The number of houses in the *Bayou* and *Near Bayou* categories is relatively small. Freedman (1981, 1984) and Freedman and Peters (1984) show that bootstrapping can improve 2SLS estimators in such situations. The procedure follows Freeman (1984), re-sampling from estimated residuals and instruments in order to retain their underlying relationship in the 2SLS environment.

All of the base model estimates exhibit the expected signs and the estimates for the base model variables are robust across the extended models. Following Kennedy (1981), the coefficient estimates imply that houses in the *Highest Risk Zone* exhibit significant price discounts of about 2.8% and longer expected selling times. The price discount is consistent with the bulk of the existing empirical literature (except Morgan (2007)) concluding that flood risk reduces property value.[9] Nonetheless, the estimates reported here clearly illustrate that focusing solely on price capitalization understates the full impact of being in a higher flood risk zone, as it overlooks the significantly greater difficulty of selling property so situated. In any case, the estimates are consistent with the notion that if flood insurance benefits are underpriced, they are not sufficiently underpriced to fully compensate for the perceived costs of flooding in the highest risk areas of Baton Rouge.

In contrast with high flood risk properties, the *Medium Risk Zone* coefficient estimates are insignificant in both price and selling time equations in all of the model versions. This is consistent with flood insurance priced equal to the risk premium of risk averse homeowners living in this zone.

Looking at the amenity effect, none of the *Bayou* coefficient estimates are significant in the price or selling time equations in table 2. Whatever the amenity value of living on the banks of a bayou or river in Baton Rouge, it is not stable enough to yield significant estimates relative to neighboring properties not so suitably situated. For waterfront properties, the flood risk dominates and the amenity effect is negligible, a result that contrasts with Morgan (2007). At the same time, the *Near Bayou* coefficients in table 2 are either significantly negative in the price equation and insignificant in the selling time equation (robust standard error model) or insignificant in the price equation and significantly positive in the selling time equation (bootstrap standard error model). This pattern indicates price discounts or less liquidity for

[9] The last parish-wide bayou and river flooding occurred in January of 1990. In order to test for differences in flood risk perceptions before and after this event, we construct a variable measuring the time since the flood event (taking a value of zero before January 1990) and add to our model the interactions of this variable and its square (to allow for a nonlinear decay rate) with *Bayou* and *Near Bayou* variables. The coefficients on these interaction variables are not statistically significant; as in Bialaszewski and Newsome (1990) and Skantz and Strickland (1987), the widespread flood experience apparently did not alter perceived flood risks. The empirical estimates for this model are available in the optional appendix.

property within 500 feet of bayous with a history of flooding. Once again, ignoring liquidity effects and concentrating solely on price effects could be misleading for these properties, depending on the error estimation method.

In order to examine the extent to which price and liquidity effects vary across the housing market cycle, we apply the repeat sales method to identify weak and strong housing market phases. The resultant price index shows the movement in house prices for the period 1984 (base year) through 2005. The housing market entered its declining phase in 1984 and prices declined for the first 20 quarters of the sample period, and remained below pre-1984 levels for a total of 36 quarters. Thereafter, the market experienced steady price increases through the rest of the sample period. Following the implications of the residential constant quality price index, we partition the full data set into a weak market phase during 1984-1992 and a strong market phase during 1993-2005. The partition is statistically significant.

Table 3 reports the flood risk variables estimates for the partitioned sample for the weak and strong market phases. Following the format in table 2, table 3 reports two sets of estimates for each market phase, one with robust errors and one with bootstrapped errors. In the weak market phase, for both models properties in the highest risk zone sell at a less than one percent discount—less than one half of the discount reported for the full sample in table 2—with no significant liquidity effect. The *Medium Risk Zone* coefficients are not significantly different from zero in either the price or selling time equations, the same as for the full sample estimates. Similarly, the *Bayou* coefficients are insignificant in price and selling time equations. The *Near Bayou* coefficients in the price equation are significantly negative in the price equation and insignificant in the selling time equation regardless of estimation method. Overall, these results are consistent with those found for the full sample.

Turning to the strong market phase estimates reported in the last four columns of table 3, the *Highest Risk Zone* and *Medium Risk Zone* coefficients differ significantly from the weak market phase estimates. Properties in the highest flood risk zone sell at a discount of over 2.8% and exhibit significantly lower liquidity than properties in the lowest risk zone. Properties in the medium flood risk zone exhibit the same pricing and liquidity as those in the least risky areas. These broad flood zone results qualitatively resemble the full sample results, with the only difference being larger price and liquidity effects in the strong market phase. In addition, the distinction between properties subject to different flood risks appears to be much more sharply drawn in the strong market phase than in the weak market phase.

Finally, consider the water view amenity and risk effects captured by the *Bayou* and *Near Bayou* variables, respectively. The only meaningful difference between the weak and strong phase results for these variables is that the flood risk appears to be capitalized primarily into the selling price in the weak market and into liquidity in the strong market. Nonetheless, the broad implications from these variables are robust across market phases in that flood risk reduces the net sales return to sellers, but whether the risk is reflected primarily in the price or difficulty of sale depends upon the market cycle.

6. Conclusion

Housing markets are search markets. In search markets, property characteristics and market conditions are reflected in two dimensions: selling price and liquidity. Starting from first principles, this paper shows why flood risks will in general be capitalized by varying degrees into house price and selling time, drawing on search theory to motivate the SUR estimator for obtaining consistent asymptotically efficient estimates of flood risk capitalization in the two dimensions.[10]

The results show significant capitalization effects in terms of both price and liquidity. In addition, the mix of capitalization in price relative to liquidity varies by type of flood risk as well as across housing market phases. Flood risk delineated by broad flood plain category is primarily capitalized into price (and the capitalization is more modest) in the weak market phase and more strongly into both selling price and selling time in the strong market phase. Localized flood risk associated with proximity to bayous and rivers, however, exhibit a slightly different pattern across market phases. These localized risks appear to be capitalized primarily into selling price in weak markets (and, again, more modestly) and primarily into selling time in strong markets. Overall, the pattern of weaker price capitalization in weak markets and stronger capitalization in strong markets is consistent with the pattern observed for the marginal value of other property attributes like living area and house age. Regardless of the specific pattern, however, the results illustrate that focusing solely on price capitalization without allowing for concomitant liquidity capitalization can understate the full impact of flood risk on house transactions.

[10] The joint determination of selling price and selling time leads to cross-equation correlation, an inefficient OLS estimator and biased standard error estimates.

Table 1. Variable Definitions and Sample Summary Statistics

Variable Name	*Definition*	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Price	Selling price of house	27939	112474.3	53422.84	40000	320000
DOM	Days on the market prior to sale	27939	86.55671	71.58518	14	400
Bedrooms	Number of bedrooms	27939	3.332295	0.606506	1	7
Bathrooms	Number of bathrooms	27939	2.024947	0.479056	1	7
Fireplaces	Number of fireplaces	27939	0.682022	0.531595	0	3
Living area	Square feet of living area	27939	1947.514	589.6457	359	4493
Net area	Square feet of total area less living area	27939	707.5496	318.8538	110	3925
Age	Age of the structure	27939	21.03139	16.08371	2	100
Age_sq	Age square	27939	700.9957	1137.184	4	10000
Living area_sq	Living area square	27939	4140480	2667262	128881	2.02E+07
Net area_sq	Net area square	27939	602290.6	638781.6	12100	1.54E+07
Vacant	Vacant house dummy variable	27939	0.299223	0.457926	0	1
Rental	Tenant occupied house dummy variable	27939	0.045063	0.207445	0	1
Listing density	Competing listings weighted by days	27939	2.534479	2.127179	0	20.14701
Smaller	Smaller than local mean living area	27939	0.069311	0.104059	0	0.888283
Larger	Larger than local mean living area	27939	0.108363	0.188227	0	2.058043
Highest Risk Zone	High flood risk category dummy variable	27939	0.241741	0.428146	0	1
Medium Risk Zone	Moderate to low flood risk category dummy variable	27939	0.23877	0.42634	0	1
Bayou	Within 300 ft. of bayou dummy variable	27939	0.060095	0.237667	0	1
Near Bayou	Within 500 ft. of bayou dummy variable	27939	0.115537	0.319675	0	1

Table 2. Seemingly unrelated regression model estimates

	Baseline model		*with flood zones*		*with flood zones and distance*			
							bootstrapped SE	
	(1)		(2)		(3)		(4)	
	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM
House characteristics								
Bedrooms	-0.0179***	0.00408	-0.0177***	-0.000850	-0.0177***	0.00738	-0.0177***	0.00738
	(0.00208)	(0.984)	(0.00207)	(0.984)	(0.00207)	(0.984)	(0.00334)	(0.985)
Bathrooms	0.0294***	0.0126	0.0297***	-0.0328	0.0297***	-0.0349	0.0297***	-0.0349
	(0.00248)	(1.173)	(0.00247)	(1.173)	(0.00247)	(1.173)	(0.00370)	(1.173)
Fireplaces	0.0209***	-3.482***	0.0211***	-3.508***	0.0212***	-3.525***	0.0212***	-3.525***
	(0.00206)	(0.976)	(0.00206)	(0.976)	(0.00206)	(0.976)	(0.00283)	(0.888)
Living area	0.000964***	0.0278***	0.000962***	0.0281***	0.000962***	0.0279***	0.000962***	0.0279***
	(1.19e-05)	(0.00562)	(1.18e-05)	(0.00562)	(1.18e-05)	(0.00562)	(2.02e-05)	(0.00382)
Net area	0.000176***	-0.0156***	0.000175***	-0.0155***	0.000175***	-0.0155***	0.000175***	-0.0155***
	(8.45e-06)	(0.00400)	(8.43e-06)	(0.00400)	(8.43e-06)	(0.00400)	(2.01e-05)	(0.00572)
Age	-0.0143***	-0.0686	-0.0142***	-0.0797	-0.0142***	-0.0786	-0.0142***	-0.0786
	(0.000198)	(0.0938)	(0.000198)	(0.0939)	(0.000198)	(0.0939)	(0.000324)	(0.0983)
Age_sq	0.000145***	0.00140	0.000144***	0.00151	0.000144***	0.00152	0.000144***	0.00152
	(2.47e-06)	(0.00117)	(2.47e-06)	(0.00117)	(2.47e-06)	(0.00117)	(3.67e-06)	(0.00129)
Living area_sq	-7.78e-08***	-2.17e-06**	-7.71e-08***	-2.26e-06**	-7.71e-08***	-2.23e-06**	-7.71e-08***	-2.23e-
	(2.30e-09)	(1.09e-06)	(2.30e-09)	(1.09e-06)	(2.30e-09)	(1.09e-06)	(4.30e-09)	(8.52e-07)
Net area_sq	-3.43e-08***	6.68e-06***	-3.38e-08***	6.62e-06***	-3.39e-08***	6.65e-06***	-3.39e-08***	6.65e-06**
	(3.94e-09)	(1.87e-06)	(3.93e-09)	(1.87e-06)	(3.93e-09)	(1.87e-06)	(1.12e-08)	(3.01e-06)
Local Marketing conditions								
Vacant	-0.0639***	10.54***	-0.0635***	10.50***	-0.0635***	10.51***	-0.0635***	10.51***
	(0.00197)	(0.935)	(0.00197)	(0.935)	(0.00197)	(0.935)	(0.00227)	(0.896)

Rental	-0.0801***	15.44***	-0.0794***	15.36***	-0.0794***	15.36***	-0.0794***	15.36***
	(0.00430)	(2.035)	(0.00429)	(2.035)	(0.00429)	(2.034)	(0.00613)	(2.953)
Smaller	0.486***	10.28	0.483***	10.51	0.483***	10.11	0.483***	10.11*
	(0.0144)	(6.840)	(0.0144)	(6.840)	(0.0144)	(6.842)	(0.0220)	(5.529)
Larger	-0.398***	7.646*	-0.401***	8.053**	-0.401***	8.026**	-0.401***	8.026**
	(0.00845)	(4.004)	(0.00844)	(4.007)	(0.00844)	(4.007)	(0.0135)	(4.004)
Listing Density	0.000510	0.452*	0.000338	0.470*	0.000344	0.467*	0.000344	0.467**
	(0.000526)	(0.249)	(0.000525)	(0.249)	(0.000525)	(0.249)	(0.000586)	(0.232)
Flood Risk conditions								
Highest Risk Zone			**-0.0281*** **	**3.472*** **	**-0.0277*** **	**3.234** **	**-0.0277*** **	**3.234*** **
			(0.00265)	**(1.259)**	**(0.00266)**	**(1.264)**	**(0.00251)**	**(1.233)**
Medium Risk Zone			**0.00388**	**0.843**	**0.00352**	**1.092**	**0.00352**	**1.092**
			(0.00340)	**(1.616)**	**(0.00341)**	**(1.621)**	**(0.00378)**	**(1.600)**
Bayou					**0.00361**	**-0.665**	**0.00361**	**-0.665**
					(0.00515)	**(2.445)**	**(0.00636)**	**(2.330)**
Near Bayou					**-0.00640**	**3.231***	**-0.00640***	**3.231**
					(0.00390)	**(1.853)**	**(0.00358)**	**(2.194)**
Constant	10.60***	44.03***	10.60***	43.69***	10.60***	43.93***	10.60***	43.93***
	(0.0195)	(9.219)	(0.0194)	(9.219)	(0.0194)	(9.219)	(0.0285)	(6.180)
Observations	27,939	27,939	27,939	27,939	27,939	27,939	27,939	27,939
R-squared	0.889	0.075	0.890	0.075	0.890	0.076	0.890	0.076

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: the table presents estimates for key variables. Estimates including year, seasonal and location controls available upon request.

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Table 3. Seemingly unrelated regression estimates for weak and strong market phases

	Falling Market				*Rising market*			
			bootstrapped				bootstrapped SE	
	(5)		(6)		(7)		(8)	
	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM
House characteristics								
Bedrooms	-0.0209***	0.804	-0.0209***	0.804	-0.0136***	-0.0128	-0.0136***	-0.0128
	(0.00357)	(1.998)	(0.00423)	(1.483)	(0.00246)	(1.102)	(0.00355)	(1.048)
Bathrooms	0.0230***	2.225	0.0230***	2.225	0.0280***	-1.212	0.0280***	-1.212
	(0.00450)	(2.516)	(0.00526)	(2.002)	(0.00287)	(1.286)	(0.00302)	(1.304)
Fireplaces	0.0437***	-0.387	0.0437***	-0.387	0.0128***	-4.434***	0.0128***	-4.434***
	(0.00379)	(2.123)	(0.00398)	(2.578)	(0.00237)	(1.063)	(0.00336)	(1.384)
Living area	0.000866***	0.0170	0.000866***	0.0170	0.00100***	0.0293***	0.00100***	0.0293***
	(2.03e-05)	(0.0114)	(2.09e-05)	(0.0113)	(1.44e-05)	(0.00647)	(2.27e-05)	(0.00863)
Net area	0.000201***	-0.00176	0.000201***	-0.00176	0.000161***	-0.0188***	0.000161***	-0.0188***
	(1.68e-05)	(0.00938)	(2.34e-05)	(0.00848)	(9.45e-06)	(0.00424)	(1.58e-05)	(0.00440)
Age	-0.0104***	-0.0199	-0.0104***	-0.0199	-0.0158***	-0.127	-0.0158***	-0.127
	(0.000408)	(0.228)	(0.000692)	(0.238)	(0.000228)	(0.102)	(0.000369)	(0.0859)
Age_sq	0.000139***	0.000227	0.000139***	0.000227	0.000157***	0.00188	0.000157***	0.00188*
	(6.42e-06)	(0.00360)	(1.53e-05)	(0.00332)	(2.73e-06)	(0.00123)	(4.18e-06)	(0.00106)
Living area_sq	-5.81e-	-1.77e-06	-5.81e-08***	-1.77e-06	-8.62e-08***	-1.65e-06	-8.62e-08***	-1.65e-06
	(3.83e-09)	(2.15e-06)	(4.13e-09)	(2.16e-06)	(2.83e-09)	(1.27e-06)	(4.56e-09)	(1.87e-06)
Net area_sq	-3.74e-	1.69e-06	-3.74e-08***	1.69e-06	-3.04e-08***	7.65e-	-3.04e-08***	7.65e-
	(8.06e-09)	(4.51e-06)	(1.31e-08)	(4.17e-06)	(4.36e-09)	(1.96e-06)	(9.46e-09)	(2.26e-06)
Local Marketing conditions								
Vacant	-0.0669***	4.311**	-0.0669***	4.311**	-0.0593***	13.26***	-0.0593***	13.26***
	(0.00333)	(1.864)	(0.00326)	(1.971)	(0.00236)	(1.058)	(0.00210)	(1.272)
Rental	-0.0733***	17.78***	-0.0733***	17.78***	-0.0775***	13.63***	-0.0775***	13.63***

	(0.00649)	(3.632)	(0.00808)	(5.147)	(0.00546)	(2.450)	(0.00980)	(2.723)
Smaller	0.463***	15.69	0.463***	15.69*	0.502***	9.019	0.502***	9.019
	(0.0251)	(14.02)	(0.0259)	(9.202)	(0.0172)	(7.729)	(0.0298)	(7.036)
Larger	-0.355***	10.29	-0.355***	10.29	-0.416***	6.566	-0.416***	6.566
	(0.0149)	(8.359)	(0.0311)	(10.17)	(0.00996)	(4.470)	(0.0119)	(6.697)
Listing Density	-0.000357	-0.711	-0.000357	-0.711*	0.00155**	1.120***	0.00155***	1.120***
	(0.000913)	(0.511)	(0.000845)	(0.427)	(0.000654)	(0.294)	(0.000539)	(0.165)
Flood Risk conditions								
Highest Risk Zone	**-0.00969****	**1.469**	**-0.00969****	**1.469**	**-0.0281*****	**4.060*****	**-0.0281*****	**4.060*****
	(0.00452)	**(2.528)**	**(0.00447)**	**(2.093)**	**(0.00320)**	**(1.436)**	**(0.00332)**	**(1.151)**
Medium Risk Zone	**0.00553**	**0.0236**	**0.00553**	**0.0236**	**0.00841****	**1.298**	**0.00841**	**1.298**
	(0.00561)	**(3.141)**	**(0.00501)**	**(3.061)**	**(0.00414)**	**(1.859)**	**(0.00516)**	**(2.581)**
Bayou	**0.00264**	**1.886**	**0.00264**	**1.886**	**-0.000462**	**-1.755**	**-0.000462**	**-1.755**
	(0.00877)	**(4.910)**	**(0.00933)**	**(4.090)**	**(0.00612)**	**(2.745)**	**(0.00545)**	**(2.876)**
Near Bayou	**-0.0158****	**0.969**	**-0.0158****	**0.969**	**-8.22e-05**	**3.979***	**-8.22e-05**	**3.979***
	(0.00669)	**(3.743)**	**(0.00659)**	**(2.755)**	**(0.00462)**	**(2.075)**	**(0.00452)**	**(2.225)**
Constant	10.05***	47.75***	10.05***	47.75***	10.61***	44.79***	10.61***	44.79***
	(0.0308)	(17.25)	(0.0324)	(15.30)	(0.0233)	(10.45)	(0.0348)	(10.25)
Observations	8,875	8,875	8,875	8,875	19,064	19,064	19,064	19,064
R-squared	0.868	0.050	0.868	0.050	0.891	0.064	0.891	0.064

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: the table presents estimates for key variables. Estimates including year, seasonal and location controls available upon request.

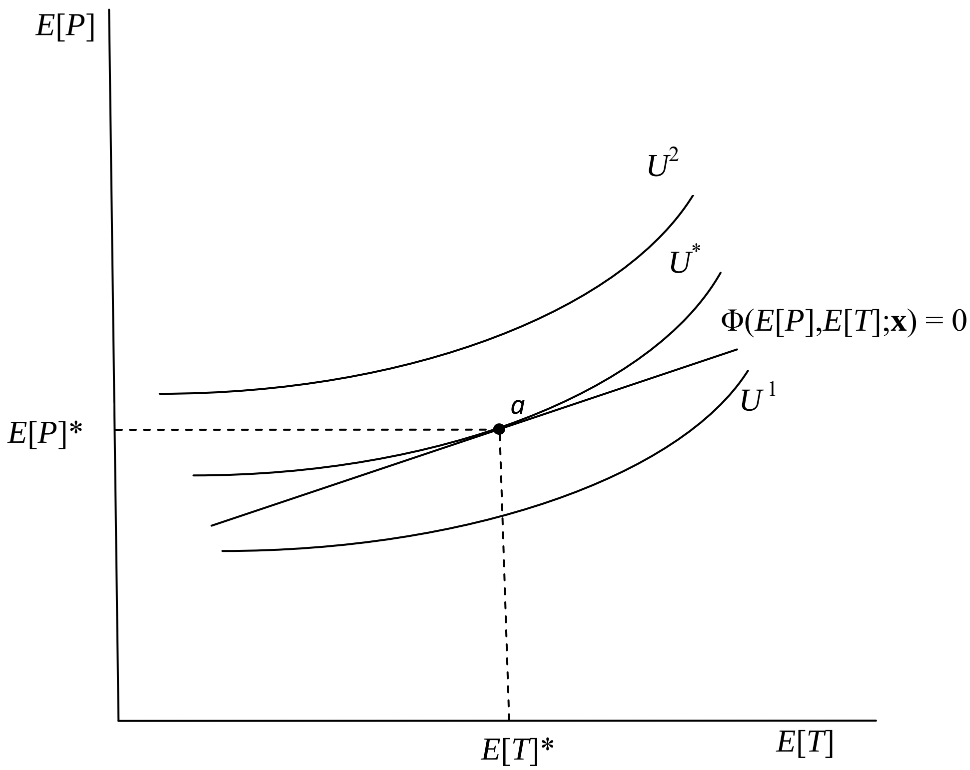

Figure 1

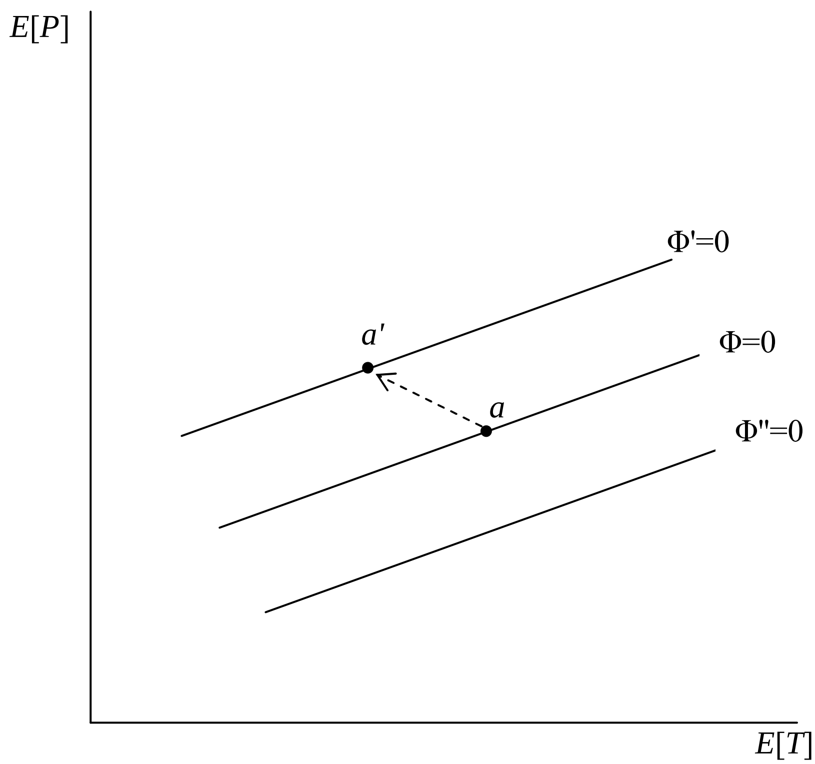

Figure 2

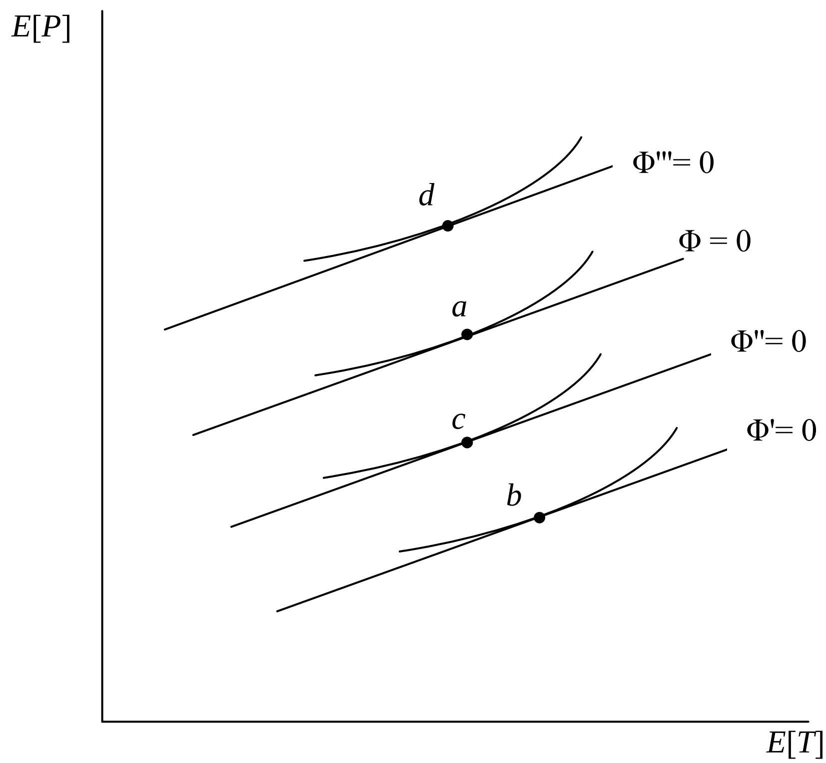

Figure 3

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Appendix

Table 1A. Seemingly unrelated regression and 3SLS model estimates
(Area based Listing Density Measures)

	With flood zones and bayous				Simultaneous model	
			Bootstrapped SE			
	(3)		(4)		(5)	
	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM
House characteristics						
Bedrooms	-0.0184***	-0.320	-0.0184***	-0.320	-0.0182***	-2.668***
	(0.00209)	(0.993)	(0.00308)	(1.044)	(0.00209)	(0.747)
Bathrooms	0.0291***	0.163	0.0291***	0.163	0.0290***	0.987
	(0.00249)	(1.183)	(0.00261)	(1.532)	(0.00249)	(0.890)
Fireplaces	0.0216***	-3.848***	0.0216***	-3.848***	0.0217***	-3.981***
	(0.00207)	(0.985)	(0.00187)	(0.924)	(0.00207)	(0.741)
Living area	0.000922***	0.0285***	0.000922***	0.0285***	0.000919***	0.0416***
	(1.21e-05)	(0.00577)	(1.86e-05)	(0.00620)	(1.22e-05)	(0.00434)
Net area	0.000173***	-0.0157***	0.000173***	-0.0157***	0.000173***	-0.0136***
	(8.46e-06)	(0.00402)	(1.73e-05)	(0.00461)	(8.46e-06)	(0.00302)
Age	-0.0136***	-0.0802	-0.0136***	-0.0802	-0.0137***	0.392***
	(0.000202)	(0.0961)	(0.000226)	(0.0813)	(0.000202)	(0.0722)
Age_sq	0.000138***	0.00152	0.000138***	0.00152*	0.000139***	-0.00391***
	(2.50e-06)	(0.00119)	(2.99e-06)	(0.000864)	(2.51e-06)	(0.000896)
Living area_sq	-7.28e-08***	-2.23e-06**	-7.28e-08***	-2.23e-06*	-7.25e-08***	-3.15e-06***
	(2.32e-09)	(1.11e-06)	(3.93e-09)	(1.25e-06)	(2.33e-09)	(8.32e-07)
Net area_sq	-3.39e-08***	6.64e-06***	-3.39e-08***	6.64e-06***	-3.40e-08***	5.61e-06***
	(3.94e-09)	(1.87e-06)	(8.74e-09)	(2.40e-06)	(3.94e-09)	(1.41e-06)
Local Marketing conditions						
Vacant	-0.0630***	10.71***	-0.0630***	10.71***	-0.0629***	4.204***
	(0.00198)	(0.944)	(0.00156)	(1.038)	(0.00198)	(0.711)
Rental	-0.0785***	15.30***	-0.0785***	15.30***	-0.0785***	9.245***
	(0.00433)	(2.060)	(0.00443)	(1.904)	(0.00433)	(1.550)
Smaller	0.419***	10.26	0.419***	10.26*	0.409***	104.0***
	(0.0146)	(6.960)	(0.0185)	(5.772)	(0.0149)	(5.215)

Larger	-0.373***	7.398*	-0.373***	7.398	-0.376***	31.11***
	(0.00866)	(4.119)	(0.0114)	(5.307)	(0.00870)	(3.101)
Distance_LSU	-0.00772***	2.234**	-0.00772***	2.234**	-0.00800***	4.767***
	(0.00204)	(0.972)	(0.00193)	(1.073)	(0.00204)	(0.730)
Distance_CBD	0.0303***	-0.194	0.0303***	-0.194	0.0305***	-0.936
	(0.00166)	(0.791)	(0.00196)	(0.872)	(0.00166)	(0.595)
Listing Density	-0.000329	0.780***	-0.000329	0.780***	-0.00161***	
	(0.000539)	(0.257)	(0.000546)	(0.282)	(0.000530)	
Competition						0.172***
						(0.00119)
Flood Risk conditions						
Highest Risk Zone	**-0.0231*** **	**2.775** **	**-0.0231*** **	**2.775*** **	**-0.0232*** **	**3.478*** **
	(0.00272)	**(1.295)**	**(0.00282)**	**(0.929)**	**(0.00272)**	**(0.974)**
Medium Risk Zone	**0.00784** **	**0.469**	**0.00784**	**0.469**	**0.00796** **	**-0.710**
	(0.00351)	**(1.668)**	**(0.00551)**	**(1.713)**	**(0.00351)**	**(1.255)**
Bayou	**0.00604**	**-1.267**	**0.00604**	**-1.267**	**0.00601**	**-2.227**
	(0.00523)	**(2.490)**	**(0.00525)**	**(2.980)**	**(0.00523)**	**(1.873)**
Near Bayou	**-0.00617**	**3.861** **	**-0.00617**	**3.861* **	**-0.00609**	**2.303**
	(0.00397)	**(1.891)**	**(0.00455)**	**(2.232)**	**(0.00397)**	**(1.422)**
Constant	10.36***	28.83**	10.36***	28.83**	10.36***	-21.40**
	(0.0295)	(14.02)	(0.0279)	(12.84)	(0.0295)	(10.52)
Observations	27,939	27,939	27,939	27,939	27,939	27,939
R-squared	0.891	0.076	0.891	0.075	0.891	0.477
Fixed effects	Block groups	Block groups	Block groups	Block groups	Block groups	Block groups

Clustered standard errors in parentheses. Clustering done based on census block groups. Coefficients for variables that capture year and season sold, and location controls based on 265 census block groups are not reported here.
*** p<0.01, ** p<0.05, * p<0.1

Table 2A. Seemingly unrelated regression and 3SLS model estimates
(Selling Price Listing Density Measure)

	With flood zones and bayous				Simultaneous model	
			Bootstrapped SE			
	(3)		(4)		(5)	
	Ln(Price)	DOM	Ln(Price)	DOM	Ln(Price)	DOM
House characteristics						
Bedrooms	-0.0184***	-0.320	-0.0184***	-0.320	-0.0183***	-2.668***
	(0.00209)	(0.993)	(0.00308)	(1.044)	(0.00209)	(0.747)
Bathrooms	0.0291***	0.163	0.0291***	0.163	0.0290***	0.987
	(0.00249)	(1.183)	(0.00261)	(1.532)	(0.00249)	(0.890)
Fireplaces	0.0216***	-3.848***	0.0216***	-3.848***	0.0217***	-3.981***
	(0.00207)	(0.985)	(0.00187)	(0.924)	(0.00207)	(0.741)
Living area	0.000922***	0.0285***	0.000922***	0.0285***	0.000921***	0.0416***
	(1.21e-05)	(0.00577)	(1.86e-05)	(0.00620)	(1.21e-05)	(0.00434)
Net area	0.000173***	-0.0157***	0.000173***	-0.0157***	0.000173***	-0.0136***
	(8.46e-06)	(0.00402)	(1.73e-05)	(0.00461)	(8.46e-06)	(0.00302)
Age	-0.0136***	-0.0802	-0.0136***	-0.0802	-0.0137***	0.392***
	(0.000202)	(0.0961)	(0.000226)	(0.0813)	(0.000202)	(0.0722)
Age_sq	0.000138***	0.00152	0.000138***	0.00152*	0.000139***	-0.00391***
	(2.50e-06)	(0.00119)	(2.99e-06)	(0.000864)	(2.50e-06)	(0.000896)
Living area_sq	-7.28e-08***	-2.23e-06**	-7.28e-08***	-2.23e-06*	-7.28e-08***	-3.15e-06***
	(2.32e-09)	(1.11e-06)	(3.93e-09)	(1.25e-06)	(2.32e-09)	(8.32e-07)
Net area_sq	-3.39e-08***	6.64e-06***	-3.39e-08***	6.64e-06***	-3.40e-08***	5.61e-06***
	(3.94e-09)	(1.87e-06)	(8.74e-09)	(2.40e-06)	(3.94e-09)	(1.41e-06)
Local Marketing conditions						
Vacant	-0.0630***	10.71***	-0.0630***	10.71***	-0.0630***	4.205***
	(0.00198)	(0.944)	(0.00156)	(1.038)	(0.00198)	(0.711)
Rental	-0.0785***	15.30***	-0.0785***	15.30***	-0.0786***	9.246***
	(0.00433)	(2.060)	(0.00443)	(1.904)	(0.00433)	(1.550)
Smaller	0.419***	10.26	0.419***	10.26*	0.414***	104.0***
	(0.0146)	(6.960)	(0.0185)	(5.772)	(0.0146)	(5.215)

Larger	-0.373***	7.398*	-0.373***	7.398	-0.374***	31.10***
	(0.00866)	(4.119)	(0.0114)	(5.307)	(0.00866)	(3.101)
Distance_LSU	-0.00772***	2.234**	-0.00772***	2.234**	-0.00792***	4.767***
	(0.00204)	(0.972)	(0.00193)	(1.073)	(0.00204)	(0.730)
Distance_CBD	0.0303***	-0.194	0.0303***	-0.194	0.0303***	-0.936
	(0.00166)	(0.791)	(0.00196)	(0.872)	(0.00166)	(0.595)
Sell Price Listing Density	-0.000329	0.780***	-0.000329	0.780***	-0.00154***	
	(0.000539)	(0.257)	(0.000546)	(0.282)	(0.000539)	
Sell Price Competition						0.172***
						(0.00119)
Flood Risk conditions						
Highest Risk Zone	**-0.0231*** **	**2.775** **	**-0.0231*** **	**2.775*** **	**-0.0233*** **	**3.477*** **
	(0.00272)	**(1.295)**	**(0.00282)**	**(0.929)**	**(0.00272)**	**(0.974)**
Medium Risk Zone	**0.00784** **	**0.469**	**0.00784**	**0.469**	**0.00771** **	**-0.710**
	(0.00351)	**(1.668)**	**(0.00551)**	**(1.713)**	**(0.00351)**	**(1.255)**
Bayou	**0.00604**	**-1.267**	**0.00604**	**-1.267**	**0.00595**	**-2.227**
	(0.00523)	**(2.490)**	**(0.00525)**	**(2.980)**	**(0.00523)**	**(1.873)**
Near Bayou	**-0.00617**	**3.861** **	**-0.00617**	**3.861* **	**-0.00615**	**2.303**
	(0.00397)	**(1.891)**	**(0.00455)**	**(2.232)**	**(0.00397)**	**(1.422)**
Constant	10.36***	28.83**	10.36***	28.83**	10.36***	-21.39**
	(0.0295)	(14.02)	(0.0279)	(12.84)	(0.0295)	(10.52)
Observations	27,939	27,939	27,939	27,939	27,939	27,939
R-squared	0.891	0.076	0.891	0.075	0.891	0.477
Fixed effects	Block groups	Block groups	Block groups	Block groups	Block groups	Block groups

Clustered standard errors in parentheses. Clustering done based on census block groups. Coefficients for variables that capture year and season sold, and location controls based on 265 census block groups are not reported here.
*** p<0.01, ** p<0.05, * p<0.1