Price Adjustment and Liquidity in a Residential Real Estate Market with an Accelerated Information Cascade

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Abstract We examine the effect of an unannounced information event, Hurricane Katrina, on the liquidity of the residential real estate market in an area proximately located to the Mississippi Gulf Coast. Using 2SLS and Weibull techniques applied to a unique MLS data set, we test changes in liquidity in a submarkets framework. Results suggest Katrina created submarket effects with respect to the listing and sales periods of our sample and market liquidity was directly influenced by this event. We suggest that this effect was tied to information flow as owners of heavily damaged properties sought new housing in a nearby area.

On August 29, 2005, Hurricane Katrina made landfall near Biloxi, Mississippi. As has been well-documented, Katrina proved to be the costliest Atlantic hurricane in the history of the United States, causing total damages in excess of an estimated $80 billion (USD). The world watched as television crews captured photographic evidence of this deadly natural disaster, which not only damaged property but also contributed to at least 1,599 deaths (estimated), making it the deadliest natural disaster since the San Francisco Earthquake of 1906.[1]

One of the most obvious effects to those living in the affected areas was the immediate shock to the populations of the distressed region. The New Orleans, Louisiana, MSA, with an estimated population of 1.3 million people before the disaster, was almost abandoned after the Lake Pontchartrain levees failed and the city flooded. Likewise, the Mississippi Gulf Coast Region (Jackson, Hancock, and Harrison Counties) sustained an incredible amount of damage that was directly related to the tidal surge and hurricane-force winds that assaulted that area. Infrastructure, businesses, and residential areas were destroyed or severely damaged, leaving inhabitants to seek alternative living space in a temporary, semi-permanent, or permanent manner.

Hurricane Katrina provides a unique case study to examine the effect of an unexpected event on residential real estate market dynamics. Prior to Katrina's landfall, no one could pinpoint the area that would be affected nor could they accurately estimate the scope of the effect Katrina would have on an entire region. This combination of factors makes Hurricane Katrina an extremely interesting information event. How did Hurricane Katrina affect areas on the periphery of the extreme devastation? The Hattiesburg, Mississippi, MSA received quite a bit of damage, but basic services were generally restored within two weeks of Katrina's landfall. Individuals who fled their destroyed or severely damaged properties on the Mississippi Gulf Coast or in Louisiana were able to relocate to the Hattiesburg area, where they could evaluate their individual situations while remaining in relatively close proximity to their domiciles.

We present this post-Katrina real estate market in the context of the theoretical model developed in Forgey, Rutherford, and Springer (1996), which models liquidity in a residential real estate setting. We construct both hedonic pricing and time-on-market models to test the impact of Hurricane Katrina on selling prices and marketing times of residential properties in the Hattiesburg, Mississippi, MSA. Our empirical tests align with theory, and our a priori expectation, which is driven by our theoretical application, is that market mechanisms will alter property prices and marketing times (and therefore liquidity) based on the effect of Hurricane Katrina.

The following section reviews the pertinent literature and presents the theoretical motivation for our study. Section Three introduces the data used to test our empirical models, and Section Four discusses the methodology for our modeling efforts and the results of our statistical models. Section Five concludes.

Literature

Residential Real Estate and Market Efficiency

The residential real estate brokerage literature is rife with studies focused on the effect of property characteristics, revealed information, marketing strategies, and other factors on property price. Sirmans, Macpherson, and Zietz (2005), Benjamin, Jud, and Sirmans (2000a, b), and Zumpano, Elder, and Anderson (2000) present exhaustive reviews of residential brokerage models. In their respective works, the authors address the impact of property characteristics, brokerage types, and market dynamics on property prices and marketing times. There are a number of interesting papers in this literature that combine sound theoretical modeling and empirical investigation and that yield insight into residential real estate markets in general, as well as the specific market being studied. We select several representative studies, all of which are valuable contributions to the literature; we focus our discussion on the relationship between information and transaction prices and/or times that those representative studies establish.

Yavas and Yang (1995) use transaction data to examine the role of listing prices as a strategic marketing mechanism. In the Yavas and Yang study, listing price is a signal of a number of factors: the seller's valuation of his or her property, the seller's relative bargaining power, and the commission structure in the local market, among other things. Yavas and Yang determine that sellers achieve mixed results in terms of marketing time when they increase their listing price above the market level. In this instance, the authors examine information, the signal of value and/or market power, and its impact on the associated transactions. The signal, though, is observable via the Multiple Listing Service (MLS); as new properties are listed on the MLS, the signal is recorded as an individual entry, and the precision of the signal affects only that particular transaction.

Springer (1996) examines seller motivation (more precisely, the level of seller motivation) and its impact on property selling prices and marketing times; the author's result suggests that transaction price is affected when sellers are highly motivated but that marketing time is affected only for properties under foreclosure. Springer also suggests that the listing price is the primary tool used by sellers to facilitate the sale of a property. Springer's study is interesting because it yields insight into the behavior of market participants that may be applied and/or tested across markets. The information regarding seller motivation that is contained in the MLS data used by Springer acts as a signal to observers—sellers are using the signaling capability of the MLS in order to facilitate their transactions. The information, however, is present in the MLS and may be deemed as individual transactions that are considered by the market piecemeal within the context of the overall market, which is relatively unaffected by the motivation of an individual seller.

In their study, Johnson, Zumpano, and Anderson (2007) examine real estate agent specialization and the effect of specialization on agent income and productivity. Results suggest that specialization in listings may be profitable but that specialization in selling is not. The authors do not explicitly examine the effect of an agent selling his or her own property.[2] They find that agents who participated in more transactions earn greater incomes. Their study highlights a particular vein of the brokerage literature—examining characteristics of individual agents that could affect agent performance and the outcome experienced by the consumer, since agent income is a product of listing and selling individual properties.

In another recent study, Rutherford, Springer, and Yavas (2004) examine agent contract type and its impact on selling price and marketing time. Using MLS data, the authors apply hedonic pricing and duration models to investigate the pertinent research questions. Contracts specifying exclusive agency relationships are found to attain higher selling prices and shorter marketing times for high-end properties and pricing discounts and extended marketing periods for low-end properties. As in Johnson, Zumpano, and Anderson (2007), Rutherford, Springer, and Yavas' contribution is identification of useful information—a method of discriminating among agents.

In these studies, as in most of the residential real estate brokerage literature, the focus is a characteristic, a strategy, or information that is applicable at the property-specific level. We propose to examine an information event, the extent of which could not be accurately foreseen, and that event's effect on the market dynamics of an associated residential real estate market. The results of our study will lend insight into residential real estate market efficiency when information arrives rapidly rather than slowly, as in an information cascade.

Information Cascade

In economics-related disciplines, cascades are processes in which there is a slow revelation of information that may affect the market value of an asset. One may visualize water trickling down a cliff and gathering in a pool below—the pool grows larger, and, as it does, the effect of the information grows as well. The reader may consult Lee (1993), Anderson and Holt (1997), and Brunnermeier (2001) for examples of applications of information cascades to markets. In essence, an information event can lead to a chain reaction of trading activity, usually beginning slowly and then spreading, picking up speed with time. In traditional asset markets, this activity is sometimes explained by the timing of the event, behavior of traders, etc. The information that sparks the cascade is one key to the overall problem.

In the cases of Yavas and Yang (1995), Springer (1996), and many other studies, the informational signal is a physical characteristic or mechanism design characteristic that is easily observable through the MLS and, as a result, participants in residential real estate markets may observe transactions involving these characteristics; as the number of transactions grows, the information regarding the characteristic's impact cascades, forming a pool of information related to that characteristic that grows as well.

Let us consider, then, information events that affect entire markets. One might suggest that changes in tax codes, changes in zoning laws, or institution of environmental restrictions on property are macro-level events that affect property value; however, these events are announced, debated, and (sometimes) voted upon by members of the community in question.[3] That is to say, the financial magnitude of these types of events is at least somewhat predictable to informed market participants, and, as a result, markets adjust to the revealed information. It is in this regard that our event of interest, Hurricane Katrina, differs from the others. The effect, and certainly the magnitude of the effect, of Hurricane Katrina were not predictable beforehand.

On the evening of August 28, 2005, the areas affected by Katrina remained unaffected, but by the morning of August 30, 2005, residents of the affected areas were discovering the degree of damage. The entire information revelation process took place in less than forty-eight hours, a period during which even peripheral residential real estate markets were inactive. This information revelation was not a cascade; it was a flood, with information moving quickly and flooding the information pool. By August 30, 2005, tens of thousands of residents of the

Mississippi Gulf Coast were aware that they must secure housing because their previous housing was either seriously damaged or destroyed. Many sought relief in proximate areas where services were less interrupted and where housing was available.

Our focus is one such peripheral MSA—the Hattiesburg, Mississippi, MSA—and that area's real estate market's response to the infusion of displaced individuals seeking housing. Hattiesburg, Mississippi, had an estimated 50,000 residents (within the corporate limits) before Hurricane Katrina's arrival.[4] Within one month post-Katrina, Hattiesburg's estimated population had added 10,000 evacuee households, representing an approximate 20% population increase directly related to Katrina.[5] How, then, did this unannounced event affect the Hattiesburg residential real estate market?[6] In the section that follows, we discuss this rather unique problem in terms of a theoretical construct.

Market Dynamics and Submarket Effects

The standard foci of residential real estate brokerage studies are selling price (in dollars) and marketing time (in days), since these are the simultaneously-determined factors in any residential real estate transaction. As such, any theoretical treatment of the issue at hand must eventually be expressed in terms of these two factors. However, the selling prices and marketing times cannot remain static through a significant information event, which provides some challenge in modeling. We must adopt a method that allows us to properly examine the potential shifts in market dynamics without sacrificing explanatory power.

We choose to model the problem in terms of submarkets.[7] If we consider the period January 1, 2005 through April 29, 2006 (which includes thirty-four work weeks prior to and subsequent to Katrina), we can divide our sample into three distinct groups: properties that were both listed and sold between January 1, 2005 and August 29, 2005; properties that listed between January 1, 2005 and August 29, 2005, but that sold between August 29, 2005, and April 29, 2006; and properties that were both listed and sold between August 29, 2005 and April 29, 2006. By stratifying our sample in this manner, we can apply the submarket methodology presented in Allen, Springer, and Waller (1995), which we discuss in detail in a subsequent section.

Market Dynamics and Liquidity

One possible framework in which to view our empirical results is the liquidity framework presented in Forgey, Rutherford, and Springer (1996), which constructs a model of market liquidity based on selling price and marketing time, making it intuitively and empirically appealing for our purposes. In essence, the model is built around three structural equations. These equations model the relationship between the seller's reservation price, the buyer's reservation price, and the offer prices in the transaction between the buyer and seller. They are:

$$\text{accept if } O_i \geq P_{rs} \text{ or reject if } O_i < P_{rs} \tag{1}$$

$$P_{rs} \leq P^* \leq P_{rb} \tag{2}$$

$$C_s = f(E); \frac{dC_s}{dE} > 0 \tag{3}$$

Equation (1) governs the seller's decision to accept a particular offer price, O_i, from a set of offer prices received over time, given that the seller compares said offer price to his/her reservation price, P_{rs}. The set of offer prices have an associated probability distribution such that the seller has some appraisal of the probability of receiving an offer of equal or greater value in the future. Hence, the seller makes his/her decision to accept or reject offers based on (1). Given that the selling process is a bargaining process, (2) describes the relationship between the seller's reservation price, P_{rs}, the transaction price, P^*, and the buyer's reservation price, P_{rb}. Equation (2) allows for all possible sets of offers, given rational market participants. Equation (3) describes the seller's cost of searching, C_s, which is an increasing function of search effort, E.

Forgey, Rutherford, and Springer (1996) make several important assumptions regarding the interaction of these structural equations. First, the buyer's search cost, C_b, and his/her effort level, E_b, are assumed constant across properties and over time, while only the seller's effort, E_s, is assumed constant for that participant. Second, the actual reservation prices for both the buyer and the seller, P_{rb} and P_{rs}, are unknown. Taking these assumptions along with Equations (1)–(3), the authors have assembled a complete model of liquidity which they apply to an examination of time on the market, T, and transaction price, P^*. As a result of their model, Forgey, Rutherford, and Springer posit that more liquid properties must exhibit higher selling prices and/or shorter marketing times:

$$\frac{dL}{dP^*} > 0 \tag{4}$$

$$\frac{dL}{dT} < 0 \tag{5}$$

As we gather our empirical results, we expect to draw conclusions regarding not only the basic empirical relationships present in our sample but also the overarching ramifications for liquidity, a necessity in any vibrant market.

Data

Our initial data set included all 1,363 conventional residential closings between January 7, 2005 and April 29, 2006 in the Hattiesburg, Mississippi, MSA.[8] The Hattiesburg Area Association of Realtors' (HAAR) MLS was the primary data source for the study, providing data on selling price, selling time, location, and the physical characteristics of listed properties. Obvious data-entry errors, such as a negative time-on-market, zero bedrooms or baths, etc., were removed from the MLS database, as were observations with missing values. In addition, observations of selling price or time-on-market greater than or less than three standard deviations from the mean were removed, so that our final data set consists of 1,090 observations. We also utilize foreclosure data from the Mortgage Bankers Association, interest rate data from the Federal Reserve Board of Governors, and unemployment data from the U.S. Bureau of the Census. Descriptive statistics are presented in Exhibit 1.[9]

Independent Variables

Our estimations are based around two specific variables: selling price and days on market. To achieve a better model fit, we model the natural logarithm of selling price (*SoldPrice*) and days-on-market (*DaysOnMarket*) as the dependent variables in our pricing and duration models presented in the methodology sections. Additionally, we use the listing price (*ListPrice*) in our time-on-market models in place of *SoldPrice*.[10]

Physical Characteristic Variables

As explanatory variables, we begin with the natural logarithm of property's age in years (*Age*), the natural logarithm of the reported square footage (*SqFt*), the natural logarithm of the number of total bedrooms (*Bedrooms*), and the natural logarithm of the number of total bathrooms (*Bathrooms*) as basic regressors. We expect, a priori, that older properties will receive a pricing discount relative to newer properties. We also expect that larger properties will receive a pricing premium in comparison to smaller properties and that more bathrooms will be positively incorporated into a property's price. Our expectation of the impact of *Bedrooms* on selling price is indeterminate. While we might expect that the number of bedrooms is unequivocally positively related to property prices, Sirmans, Macpherson, and Zietz (2005) report that, in the studies abstracted, 47.5% of studies—almost half—reported that the number of bedrooms was either negatively related to selling price or was insignificant in explaining price. No other characteristic examined by Sirmans, Macpherson, and Zietz displayed a similar lack of sign/significance definition. At worst, our empirical investigation will add to this debate.

Exhibit 1 | Selected Descriptive Statistics

Variable	Mean	Std. Dev.	Median	Minimum	Maximum
Panel A: Combined Sample					
SoldPrice	$148,090.84	$69,649.57	$135,000.00	$18,500.00	$416,000.00
ListPrice	$151,586.45	$71,241.47	$137,500.00	$19,900.00	$426,500.00
DaysOnMarket	53.97	50.24	38.00	1.00	232.00
Age	16.36	20.33	7.00	0.00	83.00
SqFt	1,891.88	556.15	1,801.00	750.00	4,001.00
Bedrooms	3.22	0.56	3.00	2.00	5.00
Bathrooms	1.99	0.50	2.00	1.00	3.00
OakGrove	0.48	0.50	0.00	0.00	1.00
Latitude	31.32	0.09	31.32	31.13	33.92
Longitude	−89.33	0.34	−89.34	−89.58	−78.11
NumBrokList	177.50	116.87	163.00	1.00	344.00
List_ForeTrend	1.06	0.68	0.64	0.56	2.44
List_UnempTrend	1.03	0.11	1.04	0.77	1.18
List_TimeTrend	6.31	3.91	6.00	0.00	15.00
List_IntTrend	1.09	0.01	1.09	1.07	1.12
Sold_ForeTrend	1.25	0.79	1.13	0.56	2.44
Sold_UnempTrend	1.01	0.14	1.04	0.77	1.18
Sold_TimeTrend	8.91	3.75	9.00	0.00	15.00
Sold_IntTrend	1.09	0.01	1.04	1.07	1.12
PCList	3.82	2.51	3.68	−0.17	8.74
PCSold	−3.89	2.27	−3.57	−7.78	1.29
Panel B: PRE Sample					
SoldPrice	$137,836.80	$63,202.39	$125,500.00	$22,200.00	$388,000.00
ListPrice	$141,431.03	$64,684.87	$128,800.00	$25,550.00	$398,000.00
DaysOnMarket	45.14	38.88	35.00	1.00	198.00
Age	16.56	20.45	7.00	0.00	81.00
SqFt	1,857.17	533.02	1,788.00	750.00	4,001.00
Bedrooms	3.21	0.55	3.00	2.00	5.00
Bathrooms	2.00	0.50	2.00	1.00	3.00
OakGrove	0.50	0.50	0.00	0.00	1.00
Latitude	31.32	0.13	31.32	31.13	33.92
Longitude	−89.32	0.55	−89.35	−89.58	−78.11
NumBrokList	181.77	118.33	211.00	1.00	344.00
List_ForeTrend	0.64	0.13	0.64	0.56	1.13

Exhibit 1 | (continued)

Selected Descriptive Statistics

Variable	Mean	Std. Dev.	Median	Minimum	Maximum
List_UnempTrend	1.01	0.03	1.00	0.98	1.17
List_TimeTrend	2.65	1.84	3.00	0.00	7.00
List_IntTrend	1.11	0.01	1.10	1.08	1.12
Sold_ForeTrend	0.81	0.27	0.64	0.56	1.13
Sold_UnempTrend	1.04	0.06	1.04	0.98	1.17
Sold_TimeTrend	4.86	1.70	5.00	0.00	7.00
Sold_IntTrend	1.09	0.01	1.09	1.08	1.12
PCList	1.42	1.12	1.60	−0.17	4.30
PCSold	−1.55	0.96	−1.73	−2.69	1.29
Panel C: PRE/POST Sample					
SoldPrice	$160,436.37	$70,559.84	$149,000.00	$18,500.00	$395,000.00
ListPrice	$164,079.85	$71,342.16	$152,000.00	$19,900.00	$395,000.00
DaysOnMarket	95.06	56.86	85.00	1.00	232.00
Age	14.52	19.79	4.00	0.00	83.00
SqFt	1,984.03	551.96	1,883.50	912.00	3,728.00
Bedrooms	3.28	0.53	3.00	2.00	5.00
Bathrooms	2.04	0.47	2.00	1.00	3.00
OakGrove	0.52	0.50	1.00	0.00	1.00
Latitude	31.32	0.03	31.32	31.15	31.42
Longitude	−89.34	0.08	−89.35	−89.57	−89.16
NumBrokList	168.24	115.28	163.00	1.00	344.00
List_ForeTrend	0.90	0.28	1.13	0.56	1.13
List_UnempTrend	1.06	0.07	1.04	0.98	1.17
List_TimeTrend	5.44	1.57	6.00	0.00	7.00
List_IntTrend	1.09	0.01	1.09	1.08	1.12
Sold_ForeTrend	1.93	0.71	2.44	0.56	2.44
Sold_UnempTrend	1.11	0.11	1.17	0.77	1.18
Sold_TimeTrend	9.61	1.46	9.00	8.00	15.00
Sold_IntTrend	1.08	0.00	1.08	1.07	1.09
PCList	3.23	1.07	3.68	−0.17	4.30
PCSold	−4.10	0.95	−3.57	−7.78	−3.29
Panel D: POST Sample					
SoldPrice	$153,088.37	$75,958.08	$137,900.00	$24,500.00	$426,500.00
ListPrice	$149,794.83	$73,691.98	$136,200.00	$27,000.00	$416,000.00

Exhibit 1 | (continued)

Selected Descriptive Statistics

Variable	Mean	Std. Dev.	Median	Minimum	Maximum
DaysOnMarket	34.24	37.58	20.00	1.00	189.00
Age	17.44	20.52	7.00	0.00	83.00
SqFt	1,862.56	575.60	1,750.00	770.00	3,892.00
Bedrooms	3.18	0.58	3.00	2.00	5.00
Bathrooms	1.94	0.52	2.00	1.00	3.00
OakGrove	0.44	0.50	0.00	0.00	1.00
Latitude	31.32	0.04	31.32	31.13	31.42
Longitude	−89.33	0.08	−89.33	−89.50	−89.12
NumBrokList	179.65	116.42	211.00	1.00	344.00
List_ForeTrend	1.60	0.84	1.13	0.56	2.44
List_UnempTrend	1.02	0.16	1.11	0.77	1.18
List_TimeTrend	10.58	1.98	10.00	7.00	15.00
List_IntTrend	1.08	0.00	1.08	1.07	1.09
Sold_ForeTrend	1.22	0.85	0.64	0.56	2.44
Sold_UnempTrend	0.91	0.14	0.87	0.77	1.18
Sold_TimeTrend	12.49	2.00	13.00	8.00	15.00
Sold_IntTrend	1.08	0.01	1.08	1.07	1.09
PCList	6.65	1.00	6.74	4.30	8.74
PCSold	−6.09	1.44	−6.59	−7.78	−3.29

Notes: The combined sample (N = 1,090) includes all properties listed and sold through the Hattiesburg, MS, MLS during the study period. The PRE sample (N = 407) includes all properties that were both listed and sold through the Hattiesburg, MS, MLS prior to Hurricane Katrina. The PRE/POST sample (N = 279) includes all properties that were both listed prior to Hurricane Katrina but sold after Hurricane Katrina through the Hattiesburg, MS, MLS. The POST sample (N = 404) includes all properties that were both listed and sold after Hurricane Katrina through the Hattiesburg, MS, MLS. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *ForeTrend* is the trend in foreclosure rates in Mississippi, *UnempTrend* is the trend is unemployment rates in Mississippi, *TimeTrend* is the overall time trend, and *IntTrend* is the trend in Mississippi interest rates. A *List* prefix indicates that the trend corresponds to a property's listing date while a *Sold* prefix indicates correspondence with a property's selling date. *PCList* is the first principal component constructed from the listing trend variables, and *PCSold* is the first principal component from the selling trend variables.

For locational reference, our model includes an explanatory indicator for the area generally considered most desirable, Oak Grove (*OakGrove*). The Hattiesburg MSA is actually comprised of three contiguous communities: Hattiesburg, Oak Grove, and Petal. Hattiesburg and Petal lie primarily in Forrest County, and both are incorporated communities. The Oak Grove area is more popular than the Hattiesburg or Petal areas because it lies primarily in unincorporated portions of Lamar County, therefore benefiting from no city taxes and lower county taxes, and because its schools are affiliated with the Lamar County system and not with the Forrest County system.[11] Thus, Oak Grove (*OakGrove*) acts as a control for location and the unobservable, instrumental characteristics that accompany location in this local real estate market. *OakGrove* loads a value of one if the property falls in the appropriate area and zero otherwise. In addition, we also include variables that represent each property's geographic latitude (*Latitude*) and longitude (*Longitude*) for more exact location control.

Market Variables

We include a number of market and economic variables as controls for the overall market conditions that were evident in the study period. These variables include two time trend variables, one related to the listing of each property (the listing time trend, or *List_TimeTrend*) and one related to the closing or selling of each property (the selling time trend, or *Sold_TimeTrend*). In each case, a value of 1 reflects an activity (listing or selling) January 2005 while a value of 16 reflects activity (listing or selling) April 2006. For example, a property that listed in January 2005 and sold in May 2005 would have a *List_TimeTrend* value of 1 and a *Sold_TimeTrend* value of 5.[12]

We also include a number of trend variables that mimic those included by Forgey, Rutherford, and Springer (1996). We include variables that track changes in foreclosure rates, unemployment rates, and interest rates. As in Forgey, Rutherford, and Springer, we calculate these trend variables to correspond to both the listing and selling dates for each property. To track foreclosure rates, we use Mortgage Bankers Association mortgage inventory data for Mississippi; our proxy for interest rates is the prime rate, taken from the Federal Reserve Bank of the U.S., and our unemployment rate is the Mississippi unemployment rate from the U.S. Bureau of Labor Statistics. As in Forgey, Rutherford, and Springer, we calculate the interest rate trend variable for the listing date using the following method:

$$List\_IntTrend = \frac{(IntRate_{-1} + IntRate_{-2} + IntRate_{-3})}{(IntRate_{-4} + IntRate_{-5} + IntRate_{-6})} \qquad (6)$$

Where the listing date is denoted as time period 0 and $IntRate_{-1}$ is defined as the prime rate for the month prior to the listing date. Other rate trends (i.e., *List_ForeTrend* and *List_UnempTrend*) are defined relative to the listing date as well. All trend variables for the selling date (i.e., *Sold_ForeTrend*, *Sold_IntTrend*, and *Sold_UnempTrend*) are calculated in a similar manner with the selling date denoted as time period 0.

Through inclusion of a breadth of explanatory variables, we hope to achieve a good model fit with appropriate explanatory power. Using trend variables for both listing and selling dates allows us to include a greater information set with respect to market variables and to have greater flexibility in modeling efforts. The following section describes the methodology that is applied to the data.[13]

Methodology and Results

Our empirical investigation is divided into two sections: the investigation of selling price and the investigation of time on the market. The following sections describe these empirical processes and the results of the modeling efforts.

Investigating Selling Price

We begin our investigation of potential changes in selling prices caused by Hurricane Katrina with a series of *t*-tests for differences in means and *F*-tests for differences in variances of *SoldPrice* across the three hypothesized submarkets.[14] We expect, ex ante, that these tests would yield some initial insight into our specific problem; a significant difference in means and/or variances of *SoldPrice* across the submarkets would seem to indicate that the dynamics of *SoldPrice* changed based on our unexpected shock (Hurricane Katrina) and would, therefore, lend credence to the application of the Allen, Springer, and Waller (1995) model to our problem. The results of these tests are presented in Exhibit 2. The results indicate that mean selling prices appear to be significantly lower for properties that sold before Katrina versus those that sold after Katrina, and the escalation in price seems to be greatest for those properties that listed before Katrina but sold afterwards. Additionally, the *F*-test results indicate that the variance of selling prices appears to be significantly lower for properties that sold before Katrina versus those that sold after Katrina.

The *t*-test results seem to indicate that, in the context of our theory, the submarket of properties listed prior to Katrina and sold after Katrina experience higher liquidity corresponding to higher prices. This elevated pricing structure seems to abate for properties in the third submarket—those listed and sold after Katrina—although the general level of prices, and, therefore, liquidity, seems to be higher in the POST submarket when compared to the PRE submarket. The *F*-test results generally bear out these same conclusions. These conclusions seem reasonable,

Exhibit 2 | Two Sample Tests—Pairwise

	Mean *SoldPrice*	Std. Dev. *SoldPrice*	*t*-Stat.	*F*-Stat.
PRE	$137,836.80	$63,202.39	−4.42***	.80**
PRE / POST	$160,436.37	$70,559.84		
PRE	$137,836.80	$63,202.39	−2.54***	.74***
POST	$149,794.83	$73,691.98		
PRE / POST	$160,436.37	$70,559.84	1.95*	.92
POST	$149,794.83	$73,691.98		

Notes: The *F*-test for is used for inequality of variances, the *t*-test is used for inequality of means. The variable of interest is *SoldPrice*. Unequal variances are assumed for *t*-tests The PRE sample includes all properties that were both listed and sold through the Hattiesburg MLS prior to Hurricane Katrina. The PRE / POST sample includes all properties that were both listed prior to Hurricane Katrina but sold after Hurricane Katrina. The POST sample includes all properties that were both listed and sold after Hurricane Katrina. The *t*-statistic is associated with a simple difference of means test between the appropriate pair of subsamples. For example, the first *t*-statistic listed of −4.42 indicates that there is a significant difference in the means of *SoldPrice* of the PRE sample and the PRE / POST sample at the 1% level. The *F*-statistic is associated with a difference of variances test between the appropriate pair of subsamples. For example, the first *F*-statistic of .80 indicates that the variances of *SoldPrice* for the PRE sample and the PRE / POST sample are significantly different at the 5% level. Overall, the results of the t-tests indicate that the mean *SoldPrice* peaked after Hurricane Katrina and eventually settled to a level that remained higher than the pre-Katrina level. The *F*-tests indicate that the variance of *SoldPrice* increased after Hurricane Katrina. These results are indicative of a change in market liquidity under our adopted theoretical model.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

since the documented influx of potential consumers into our sample market (and the increased demand they represent) coincides with a decrease in supply caused by an increase in damaged, and, therefore, (at least temporarily) unmarketable, properties. It stands to reason, then, that marketable properties would enjoy greater liquidity in the face of increased demand. We view these results as supportive of our theory.

The second stage in our investigation of selling prices is application of a formal econometric model. We would prefer to use, for the purposes of this section, a two-stage least squares (2SLS) model with the first stage carrying the functional form:

$$
\begin{aligned}
\ln DaysOnMarket = {} & \eta_0 + \eta_1 \ln Age + \eta_2 \ln SqFt \\
& + \eta_3 \ln Bedrooms + \eta_4 \ln Bathrooms \\
& + \eta_5 OakGrove + \eta_6 \ln Latitude \\
& + \eta_7 \ln Longitude + \eta_8 NumBrokList \\
& + \eta_9 List\_TimeTrend + \eta_{10} List\_Winter \\
& + \eta_{11} List\_Spring + \eta_{12} List\_Summer \\
& + \eta_{13} List\_ForeTrend + \eta_{14} List\_IntTrend \\
& + \eta_{15} List\_UnempTrend + \eta_{16} \ln ListPrice \\
& + \upsilon, \qquad (7)
\end{aligned}
$$

which would yield estimates of ln*DaysOnMarket* (call these $\hat{D}$), which would be used in the second stage equation:

$$
\begin{aligned}
\ln SoldPrice = {} & \beta_0 + \beta_1 \ln Age + \beta_2 \ln SqFt + \beta_3 \ln Bedrooms \\
& + \beta_4 \ln Bathrooms + \beta_5 OakGrove + \beta_6 \ln Latitude \\
& + \beta_7 \ln Longitude + \beta_8 NumBrokList \\
& + \beta_9 Sold\_TimeTrend + \beta_{10} Sold\_Winter \\
& + \beta_{11} Sold\_Spring + \beta_{12} Sold\_Summer \\
& + \beta_{13} Sold\_ForeTrend + \beta_{14} Sold\_IntTrend \\
& + \beta_{15} Sold\_UnempTrend + \beta_{16} \hat{D} + \varepsilon. \qquad (8)
\end{aligned}
$$

This system would approximately mimic the method used by Forgey, Rutherford, and Springer (1996). Of course, we would apply this model to our full sample and to the three hypothesized submarkets. We could then use tests outlined in Allen, Springer, and Waller (1995) to determine the extent of submarket distinction and the liquidity effects present in each submarket.

When applied to our data, however, some significant econometric issues arise. The first econometric issue that arises from fitting Equations (7) and (8) is the presence of significant heteroscedasticity in our data for the combined sample and for all three hypothesized submarkets. A White's (1980) test for heteroscedasticity indicates that heteroscedasticity is a significant problem in our data. To adjust for this, we apply White's correction for heteroscedasticity in all subsequent linear modeling efforts.

A second issue that arises in using the standard 2SLS method to obtain coefficient estimates for Equations (7) and (8) is a bias in those estimates. In both the pricing equation and the time-on-market equation, the trend and seasonality variables are associated with high Variance Inflation Factors (VIFs) and notably biased coefficient estimates.[15] This is not an unexpected outcome, given that movements in the values used to calculate the trend variables were generally unidirectional (i.e., generally increasing or generally decreasing) during our relatively short time frame.

To correct this collinearity, we employ Principal Components Analysis (PCA). Specifically, we create two principal components, one corresponding to the listing trend variables and one corresponding to the selling trend variables:

$$\begin{aligned} PCList = {} & .505526*List\_ForeTrend \\ & + .174412*List\_UnempTrend \\ & + .596207*ListTT - .598799*List\_IntTrend. \end{aligned} \tag{9}$$

$$\begin{aligned} PCSold = {} & .237100*Sold\_ForeTrend \\ & + .527798*Sold\_UnempTrend \\ & - .597219*Sold\_TimeTrend \\ & + .555466*Sold\_IntTrend. \end{aligned} \tag{10}$$

These principal components are the first components calculated for each group of variables using standard PCA methodology as described in Greene (1993, pp. 271–73). After implementing the PCA-produced variables, VIFs and condition numbers return to acceptable levels (i.e., low VIFs and condition numbers less than 10). Use of PCA has its costs, however, as we will be unable to interpret the estimated coefficient corresponding to *PCList* and *PCSold* in a manner that will inform us as to the exact effects of the underlying trend variables. We have chosen to use the PCA method despite this limitation, since using the principal components will allow us to include all of the information from the underlying trend variables in our modeling process.[16]

After altering our methodology in these ways, we apply the 2SLS approach using the following equations:

$$\begin{aligned}\ln DaysOnMarket = {} & \eta_0 + \eta_1 \ln Age + \eta_2 \ln SqFt \\ & + \eta_3 \ln Bedrooms + \eta_4 \ln Bathrooms \\ & + \eta_5 OakGrove + \eta_6 \ln Latitude \\ & + \eta_7 \ln Longitude + \eta_8 NumBrokList \\ & + \eta_9 PCList + \eta_{16} \ln ListPrice + \upsilon, \end{aligned} \tag{11}$$

which yields the estimated value of ln*DaysOnMarket*, $\hat{D}$ for use in the second stage:

$$\begin{aligned}\ln SoldPrice = {} & \beta_0 + \beta_1 \ln Age + \beta_2 \ln SqFt + \beta_3 \ln Bedrooms \\ & + \beta_4 \ln Bathrooms + \beta_5 OakGrove \\ & + \beta_6 \ln Latitude + \beta_7 \ln Longitude \\ & + \beta_8 NumBrokList + \beta_9 PCSell + \beta_{16} \hat{D} + \varepsilon. \end{aligned} \tag{12}$$

In summary, our methodology for estimating the selling price equation involves (1) a 2SLS approach, (2) White's correction for heteroscedasticity, and (3) use of PCA to mitigate collinearity issues. We estimate the models for the overall time period, for the PRE submarket, for the PRE/POST submarket, and for the POST submarket. The results of the second stage (the pricing models) are presented in Exhibit 3 and discussed in the following paragraphs.

Overall Study Period

As reported in Exhibit 3, the results of the overall *F*-test ($F = 370.83$, $p < .01$) indicate that the proposed model is appropriate. Additionally, the R-squared value (.8171) and Adjusted R-squared value (.8149) are significantly high, indicating that the model demonstrates good explanatory power. Further, the VIFs for all of the explanatory variables (unreported in Exhibit 3) are less than 5.00, a fact that generally suggests that no collinearity problems exist in the model.[17] The results for each of the explanators are discussed in the order in which they appear in Exhibit 3.

The coefficient estimate corresponding to ln*Age* is both negative and statistically significant at the $\alpha = .01$ level, indicating that older properties receive a pricing discount relative to newer properties. ln*SqFt* corresponds to a positive and statistically significant coefficient estimate ($\alpha = .01$), which signifies that larger

Exhibit 3 | 2SLS Results—Second Stage Coefficients

	Combined	PRE	PRE / POST	POST
Intercept	16.9440	38.0581	103.4763**	10.9329
ln*Age*	−0.0606***	−0.0348***	−0.0689***	−0.0645***
ln*SqFt*	1.0866***	0.9493***	0.9994***	1.1143***
ln*Bedrooms*	−0.0254	−0.0156	0.0275	−0.0830
ln*Bathrooms*	0.2440***	0.2830***	0.3281***	0.2192***
OakGrove	0.1223***	0.1676***	0.1225***	0.1035***
ln*Latitude*	−3.6164	−9.8104	−30.2279**	−0.7501
ln*Longitude*	−0.5198	−0.3363	1.6205	−2.1860
NumBrokList	0.0000	−0.0001	0.0002*	0.0001
PCSold	−0.0268***	−0.0402***	−0.0080	−0.0216**
$\hat{D}$	0.0661***	0.2518***	0.237***	0.0697***
N	1,090	407	279	404
R^2	.8126	.7869	.8381	.8365
Adj. R^2	.8109	.7815	.8321	.8324
Overall F	467.93***	146.24***	138.77***	201.09***

Notes: The dependent variable is *lnSoldPrice*. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCSold* is the first principal component from the selling trend variables *Sold_ForeTrend*, *Sold_UnempTrend*, *Sold_TimeTrend*, and *Sold_IntTrend*. $\hat{D}$ is the predicted value of ln*DaysOnMarket* from the first stage of the 2SLS procedure. Variables generally carry the sign and significance predicted by existing literature. Note that properties in the highly desirable *OakGrove* area receive a pricing premium irrespective of sample or subsample. The sign and significance of *NumBrokList* for properties that were on the market during Hurricane Katrina indicates a slight brokerage effect. Market and trend variables, represented by *PCSold*, are significant overall and for properties marketed entirely before and entirely after Hurricane Katrina, but properties that were on the market during Katrina seem unaffected by these factors. The sign and significance of $\hat{D}$ indicates a tradeoff between selling price and marketing time. The output of these 2SLS regressions is used in the calculations for the Chow and Tiao-Goldberger tests in Exhibits 4 and 5.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

properties are priced higher than smaller properties, all else equal. Both of these results are expected, given the results of prior residential housing studies. An unexpected result corresponds to the variable ln*Bedrooms*. The estimated coefficient for ln*Bedrooms* is statistically insignificant, which suggests that the number of bedrooms is a statistically unimportant factor in pricing properties within our sample area. Bathrooms (as represented by ln*Bathrooms*), however, are an important factor in the pricing estimation. Results suggest that the number of

Exhibit 3.1 | Marginal Effects for *PCSold* Components in Exhibit 3

Component	Construction Coeff.	Marginal Effect[18]
Sold_ForeTrend	0.2371	\$1.15
Sold_IntTrend	0.5555	\$0.98
Sold_TimeTrend	−0.5972	\$0.55
Sold_UnempTrend	0.5278	\$1.02

Notes: The marginal effect is the effect of a 1% change in most recent component of the individual trend on *SoldPrice* for the combined sample. *Sold_ForeTrend* is the trend in foreclosure rates in Mississippi, *Sold_UnempTrend* is the trend is unemployment rates in Mississippi, *Sold_TimeTrend* is the overall time trend, and *Sold_IntTrend* is the trend in Mississippi interest rates. The *Sold* prefix indicates correspondence with a property's selling date.

bathrooms increases the selling price significantly (α = .01), a result that supports anecdotal evidence from the market in question.

As presented in our prior discussion, we expected *OakGrove* to be a significant and positive factor in pricing properties due to its preferable location, governmental structure, and school offerings, and the statistical results bear this out. At the α = .01 level, a particular property in the Oak Grove area demands a significantly higher price than an identical property in either the Hattiesburg area or the Petal area. The other location variables, which provide latitude (ln*Latitude*) and longitude (ln*Longitude*) information for each property, are both statistically insignificant.

The first of the market variables included in the estimation is *NumBrokList*, the number of listings held by the property in question's listing brokerage firm. *NumBrokList* is included as a control for size of the listing firm's operations, and its estimated effect is also statistically insignificant. Our constructed variable, *PCSold*, is negative and statistically significant at the .01 level, and Exhibit 3.1 presents the marginal effects of the *PCSold* components on *SoldPrice*.[18] We do conjecture, however, that our results suggest that healthy economic indicators are related to higher selling prices during this period in this particular market. With respect to timing, none of the seasonal indicators is statistically significant.

The instrument from the first stage of the 2SLS process, $\hat{D}$, is positive and statistically significant, however. This result suggests that longer predicted time-on-market is associated with higher selling prices, a conclusion that supports many previous works, including Forgey, Rutherford, and Springer (1996), and that indicates the recognized tradeoff between price and marketing time. We next turn our attention to the second stage results for the three hypothesized submarkets. In each instance, and with the exception of $\hat{D}$, we forego discussion of individual variables unless they contradict the results from the overall sample.

Notable Results from Submarket Estimations

In the PRE/POST estimation, the coefficient for *NumBrokList* is positive and significant. As *NumBrokList* represents the number of total listings taken by the property's listing brokerage firm during the sample period, it appears that firms that take more listings (i.e., "larger" firms) obtained higher selling prices than their smaller counterparts. Examination of Exhibit 3 indicates that this result does not hold for the combined sample or for the PRE or POST submarkets. It seems, then, that there may have been an additional brokerage pricing effect for properties that were "on the market" on our event date and that this result is in some way related to brokers who specialize in listings. This result supports the results of Johnson, Zumpano, and Anderson (2007), as well as Salter, Johnson, and King (2008).

It should also be noted that, unlike the other models, *PCSold* is statistically insignificant in explaining selling price. This could be indicative of the fact that the local market environment trumped the macro environment during the PRE/POST period. The fitted value of ln*DaysOnMarket* is once again a positive and statistically significant predictor of selling price. While our 2SLS results support the supposition that a shift in the market pricing dynamics occurred, we must conduct Chow (1960) and Tiao-Goldberger (1962) tests to determine whether or not these shifts actually occurred. Our initial hypothesis that a submarket effect was created, however, is supported by the 2SLS results as they appear in Exhibit 3.

Results of Chow Tests and Tiao-Goldberger Tests

The results of the Chow tests for structural change in pricing models are presented in Exhibit 4. The Chow test tests whether any of the variable coefficients or all of the variable coefficients are different in subsets of the data. We have three hypothesized submarkets, so we have three pairwise Chow tests. As illustrated in Exhibit 4, comparisons of the submarkets (PRE with PRE/POST, PRE/POST with POST, and PRE with POST) indicates that there was significant (α = .01) structural change in the pricing model across the three subsamples. This is strong evidence to suggest the existence of submarkets in our study.

Exhibit 5 reports the results of the Tiao-Goldberger tests. The Tiao-Goldberger test determines which model coefficients change across submarkets. As Exhibit 5 indicates, with the exception of ln*Bedrooms*, all of the model coefficients changed significantly across all three submarkets. Indeed, even ln*Bedrooms* exhibited a statistically significant shift in its coefficient estimate when comparing the

Exhibit 4 | Chow Tests for Structural Change

	PRE PRE/POST	PRE/POST POST	PRE POST
Chow F	2.52***	19.16***	12.47***

Notes: The dependent variable is ln*SoldPrice*. The Chow Test tests whether a significant structural change took place in the model of ln*SoldPrice* or not. The PRE sample includes all properties that were both listed and sold through the Hattiesburg MLS prior to Hurricane Katrina. The PRE/POST sample includes all properties that were both listed prior to Hurricane Katrina but sold after Hurricane Katrina. The POST sample includes all properties that were both listed and sold after Hurricane Katrina. Results indicate that significant structural change occurred across our three hypothesized submarkets, and these results support the submarkets hypothesis.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

PRE/POST submarket to the POST submarket. Again, this is highly suggestive of submarkets existing in the form we have hypothesized.

Investigating Time-on-Market

As a step that is analogous to our methodology for selling price, we begin our investigation of time-on-market by conducting exploratory tests with *DaysOnMarket* as the variable of interest. The results of these preliminary tests, contained in Exhibit 6, indicate that the average value of *DaysOnMarket* did, in fact, change across the three submarkets, and that the variance of *DaysOnMarket* changed as well.

Time-on-market increased for properties that were on the market during Katrina, and properties that were marketed entirely after Katrina enjoyed the shortest average marketing periods of the three hypothesized submarkets. In terms of the theoretical liquidity model's prediction regarding time-on-market, the results from Exhibit 6 indicate that liquidity may have decreased immediately following Katrina but that liquidity may also have increased to a new (and greater) level in the third submarket.

For our duration modeling, we again must control for endogenous selling price in our market time estimates. To do so, we use ln*ListPrice* as our instrumental variable.[19] Again, our models suffer from the heteroscedasticity and collinearity issues discussed in the previous sections. Our final models for the 2SLS estimations are

Exhibit 5 | Tiao-Goldberger *F*-Values for Independent Variables

	PRE PRE / POST	PRE / POST POST	PRE POST
Intercept	12.75***	16.87***	4.23**
ln*Age*	57.19***	28.12***	51.34***
ln*SqFt*	10.60***	13.23***	19.53***
ln*Bedrooms*	2.39	4.85**	2.63
ln*Bathrooms*	4.57**	8.79***	4.64**
OakGrove	6.85***	3.93**	9.58***
ln*Latitude*	14.63***	19.33***	4.99**
ln*Longitude*	4.33**	8.15***	3.64*
NumBrokList	24.97***	10.74***	20.54***
PCSold	23.18***	9.76***	12.17***
$\hat{D}$	54.95***	43.04***	48.87***

Notes: The dependent variable is ln*SoldPrice*. The Tiao-Goldberger test tests whether a significant structural change in ln*SoldPrice* took place with respect to each explanatory variable or not. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCSold* is the first principal component from the selling trend variables *Sold_ForeTrend*, *Sold_UnempTrend*, *Sold_TimeTrend*, and *Sold_IntTrend*. $\hat{D}$ is the predicted value of ln*DaysOnMarket* from the first stage of the 2SLS procedure. Note that, with the exception of ln*Bedrooms*, all of the explanatory variables exhibited significant structural change with regard to our hypothesized submarkets. ln*Bedrooms* exhibited some statistical change for properties that were on the market during Hurricane Katrina. These results support the concept of submarkets in our study.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

$$\begin{aligned} \ln ListPrice = {} & \beta_0 + \beta_1 \ln Age + \beta_2 \ln SqFt + \beta_3 \ln Bedrooms \\ & + \beta_4 \ln Bathrooms + \beta_5 OakGrove + \beta_6 \ln Latitude \\ & + \beta_7 \ln Longitude + \beta_8 NumBrokList \\ & + \beta_9 PCSell + \varepsilon, \end{aligned} \tag{13}$$

which yields the estimated value of ln*ListPrice*, $\hat{L}$ for use in the second stage:

Exhibit 6 | Two Sample Tests—Pairwise

	Mean *DaysOnMarket*	Std. Dev. *DaysOnMarket*	*t*-Stat.	*F*-Stat.
PRE	45.14	38.88	−13.13***	.47***
PRE / POST	95.06	56.86		
PRE	45.14	38.88	4.16***	1.07
POST	34.24	37.58		
PRE / POST	95.06	56.86	16.12***	2.29***
POST	34.24	37.58		

Notes: The *F*-test for is used for inequality of variances, the *t*-test is used for inequality of means. The variable of interest is *DaysOnMarket*. Unequal variances are assumed for *t*-tests. The PRE sample includes all properties that were both listed and sold through the Hattiesburg MLS prior to Hurricane Katrina. The PRE / POST sample includes all properties that were both listed prior to Hurricane Katrina but sold after Hurricane Katrina. The POST sample includes all properties that were both listed and sold after Hurricane Katrina. The *t*-statistic is associated with a simple difference of means test between the appropriate pair of subsamples. For example, the first *t*-statistic listed of −13.1287 indicates that there is a significant difference in the mean of *DaysOnMarket* of the PRE sample and the PRE / POST sample at the 1% level. The *F*-statistic is associated with a difference of variances test between the appropriate pair of subsamples. For example, the first *F*-statistic of .47 indicates that the variances of *DaysOnMarket* for the PRE sample and the PRE / POST sample are significantly different at the 1% level. Overall, the results of the t-tests indicate that the mean *DaysOnMarket* peaked after Hurricane Katrina and eventually settled to a level that remained higher than the pre-Katrina level. The F-tests indicate that the variance of *DaysOnMarket* increased after Hurricane Katrina but decreased to pre-Katrina levels. These results are indicative of a change in market liquidity under our adopted theoretical model.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

$$\begin{aligned} \ln DaysOnMarket = {} & \eta_0 + \eta_1 \ln Age + \eta_2 \ln SqFt \\ & + \eta_3 \ln Bedrooms + \eta_4 \ln Bathrooms \\ & + \eta_5 OakGrove + \eta_6 \ln Latitude \\ & + \eta_7 \ln Longitude + \eta_8 NumBrokList \\ & + \eta_9 PCList + \eta_{16} \hat{L} + \upsilon. \end{aligned} \tag{14}$$

The results of the second stage (the pricing models) are presented in Exhibit 7. In addition to the 2SLS models, we also fit two duration (survival) models. The

Exhibit 7 | 2SLS Results—Second Stage Coefficients

	Combined	PRE	PRE / POST	POST
Intercept	−264.1566**	−454.0003***	95.0421	−68.4442
ln*Age*	−0.0719***	0.0083	−0.0587*	−0.0818**
ln*SqFt*	0.3565	−0.0079	0.4033	0.2444
ln*Bedrooms*	0.0345	0.5638*	−0.3788	−0.1495
ln*Bathrooms*	−0.2081	−0.1351	−0.3900	0.0141
OakGrove	−0.1212	0.0305	−0.3013**	−0.2267
ln*Latitude*	77.0369**	138.4558***	−23.0848	17.0901
ln*Longitude*	−0.9866	−8.5780	−6.3529	4.1969
NumBrokList	−0.0010***	−0.0003	−0.0005	−0.0017***
PCList	−0.1849***	−0.4014***	−0.4281***	−0.3750***
$\hat{L}$	0.2620	0.0764	0.2693	0.3292
N	1,090	407	279	404
R^2	.1812	.2289	.3392	.1509
Adjusted R^2	.1740	.2102	.3125	.1304
Overall *F*	25.27***	12.23***	12.68***	7.36***

Notes: The dependent variable is ln*DaysOnMarket*. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCList* is the first principal component from the listing trend variables *List_ForeTrend, List_UnempTrend, List_TimeTrend*, and *List_IntTrend*. $\hat{L}$ is the predicted value of ln*ListPrice* from the first stage of the 2SLS procedure. Variables generally carry the sign and significance predicted by existing literature. Note that properties in the highly desirable *OakGrove* area that were on the market during Hurricane Katrina sell faster than their counterparts. *NumBrokList* indicates that there may be a slight brokerage effect at work. Market and trend variables, represented by *PCSold*, are significant overall and for all three submarkets. The output of these 2SLS regressions is used in the calculations for the Chow and Tiao-Goldberger tests in Exhibits 8 and 9.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

existing literature provides some debate regarding linear versus hazard modeling efforts. We provide both types of models as a means to paint the broadest possible picture of our chosen problem and its possible results. Marketing time estimation using life testing or hazard modeling was introduced by Jud, Seaks, and Winkler (1996). An alternative to OLS/2SLS, hazard modeling assumes an underlying distribution that is not normal. Our analysis will assume that time-on-market follows a Weibull distribution and will fit the following functional form to the standard Weibull hazard function:

Exhibit 7.1 | Marginal Effects for *PCList* Components in Exhibit 7
Effect on *DaysOnMarket*
Combined Sample

Component	Construction Coeff.	Marginal Effect[18]
List_ForeTrend	.5055	1.35 days
List_IntTrend	−.5988	1.03 days
List_TimeTrend	.5962	1.82 days
List_UnempTrend	.1744	1.00 day

Notes: The combined sample is used for the table. The marginal effect is the effect of a 1% change in the most recent component of the individual trend on *DaysOnMarket*. *List_ForeTrend* is the trend in foreclosure rates in Mississippi, *List_UnempTrend* is the trend in unemployment rates in Mississippi, *List_TimeTrend* is the overall time trend, and *List_IntTrend* is the trend in Mississippi interest rates. The *List* prefix indicates correspondence with a property's listing date.

$$\begin{aligned} f(X\beta) = {} & \eta_0 + \eta_1 \ln Age + \eta_2 \ln SqFt + \eta_3 \ln Bedrooms \\ & + \eta_4 \ln Bathrooms + \eta_5 OakGrove + \eta_6 \ln Latitude \\ & + \eta_7 \ln Longitude + \eta_8 NumBrokList \\ & + \eta_9 PCList + \eta_{16} \hat{L} + v. \end{aligned} \tag{15}$$

With all variables defined as before, this estimation may yield further insight into the price/time relationship. Again, the underlying distribution is not normal; the Weibull model must be considered in a manner separate from the 2SLS models. In an effort to circumvent latent heterogeneity in the underlying data, we provide the heterogeneity-corrected model from Greene (1990, pp. 724–25) based on (15). In addition to the model coefficients estimated in each case, we provide marginal effects for the more appropriate estimation (i.e., for the better of the two Weibull models).

Overall Study Period

The 2SLS model is characterized by an overall F-statistic of 25.27, which is statistically significant at the $\alpha = .01$ level. While the R^2 (.1812) and the Adjusted R^2 values (.1740) are much lower than are seen in the pricing models, these values are not significantly lower than values found in many other linear models of time-on-market. We progress with the knowledge that the model is appropriate.

Since we are now interested in marketing time rather than in selling price, the trend variables are now based on listing date relationships rather than on selling date relationships; however, the bulk of the explanatory variables remain. ln*Age* is a negative and statistically significant predictor of ln*DaysOnMarket*, indicating that, for the entire sample period, older properties sell faster than newer counterparts. This result is somewhat curious, but could be explained by an anecdotal issue: older properties are often viewed as possessing better-quality construction in our sample area. It could be, however, that this effect is submarket-sensitive.

ln*Latitude*, the representative for the property's latitude, is positively related to time-on-market. Recalling the discussion of ln*Latitude* from the pricing model, this is not surprising. Since the study area's more popular areas (and newer areas) are in the southern portions of the geographic area, properties to the north (with larger values of latitude) would be expected to undergo longer marketing periods. The number of total listings held during the sample period by a property's listing brokerage, *NumBrokList*, reduces marketing time significantly. This is an interesting result that points to the benefits of listing specialization; it appears that brokerage firms that list more properties have a tendency to shorten the marketing period. Finally, the principal component formed from the listing trend variables, *PCList*, is negative and statistically insignificant. However, the exact meaning of this is difficult to disentangle by examining coefficients. In a later section, we examine the impact of the underlying trends using a marginal effects approach. Exhibit 7.1 presents the marginal effects of a change in the components of *PCList* on ln*DaysOnMarket*.[20] We omit further discussion of the impact of these underlying factors, believing that the economic impact is inferable with coefficients and the information provided in Exhibit 7.1.

Notable Results from Submarket Estimations

The brokerage variable, *NumBrokList*, is insignificant in the PRE and PRE/POST samples, but brokerage size exhibits an effect in the combined sample and in the POST sample; properties listed by brokerage firms with a large number of listings exhibit a shorter marketing period than properties listed by brokerage firms with a smaller numbers of listings. Also, properties in the desirable Oak Grove (*OakGrove*) area exhibit shorter marketing periods in the PRE/POST submarket, the submarket with the highest level of hypothesized uncertainty.

Results of Chow Tests and Tiao-Goldberger Tests

Exhibit 8 presents the Chow *F*-values, which are all statistically significant at the $\alpha = .01$ level. Exhibit 9 presents the Tiao-Goldberger *F*-values for changes in specific explanatory variables. While the results in Exhibit 9 are not as widespread as were presented in Exhibit 5 or the 2SLS pricing model, there are some important variables that experience significant changes, including the coefficients related to age, bedrooms, location, and brokerage.

Exhibit 8 | Chow Tests for Structural Change

Dependent = *lnDaysOnMarket*

	PRE PRE / POST	PRE / POST POST	PRE POST
Chow F	20.10***	2.94***	3.87***

Notes: The dependent variable is *lnDaysOnMarket.* The Chow Test indicates that a significant structural change took place in the model of ln*DaysOnMarket.* The PRE sample includes all properties that were both listed and sold through the Hattiesburg MLS prior to Hurricane Katrina. The PRE / POST sample includes all properties that were both listed prior to Hurricane Katrina but sold after Hurricane Katrina. The POST sample includes all properties that were both listed and sold after Hurricane Katrina. Results indicate that significant structural change occurred across our three hypothesized submarkets, and these results support the submarkets hypothesis.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

Discussion of Weibull Model Results

Exhibit 10 contains the standard Weibull model results for time-on-market, while Exhibit 11 presents the heterogeneity-corrected version of the duration model. We discuss the heterogeneity-corrected version first. In Exhibit 11, we present the results of the Weibull model with heterogeneity correction for the combined sample and for the three submarket samples. Our immediate concern is the heterogeneity parameter, θ. If the value of θ is zero, then no heterogeneity exists in our data and the usual Weibull model is more appropriate. If, however, θ is not zero, then heterogeneity exists and we must use the corrected coefficients presented in Exhibit 11. For the combined sample, our estimate of $\theta = .00979$, but this value is not significantly different than zero at the .10 significance level. The θ values for the PRE, PRE/POST, and POST submarkets follow a similar pattern. Hence, we abandon the Weibull model with heterogeneity correction in favor of the usual Weibull model.

The log-likelihood values for all four models are properly signed and have some significant magnitude. The 95% confidence interval for the p-value of the combined model suggests that the Weibull model is preferred to the exponential ($1.0305 \leq p \leq 1.1427$). For the combined, PRE, and PRE/POST samples, the value of p is significantly greater than one, indicating positive duration dependence, which means that that a property's probability of sale increases with time on market. p is significantly less than one for the POST sample, which indicates negative duration dependence and indicates that a property's chances of selling decrease with time-on-market.

Exhibit 9 | Tiao-Goldberger F-Values for Independent Variables

	PRE PRE / POST	PRE / POST POST	PRE POST
Intercept	7.43***	2.58	3.73*
ln*Age*	3.61*	3.11*	3.84*
ln*SqFt*	0.83	0.32	0.36
ln*Bedrooms*	4.62**	1.59	2.37
ln*Bathrooms*	0.81	1.05	0.45
OakGrove	3.14*	1.01	1.64
ln*Latitude*	7.19***	2.45	3.88**
ln*Longitude*	0.19	0.50	0.57
NumBrokList	1.30	3.80*	4.27**
PCList	0.32	0.50	0.26
$\hat{L}$	0.51	0.27	0.50

Notes: The dependent variable is *lnDaysOnMarket*. The Tiao-Goldberger Test tests whether a significant structural change in ln*DaysOnMarket* took place with respect to each explanatory variable or not. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCList* is the first principal component from the listing trend variables *List_ForeTrend*, *List_UnempTrend*, *List_TimeTrend*, and *List_IntTrend*. $\hat{L}$ is the predicted value of ln*ListPrice* from the first stage of the 2SLS procedure. Note that very few of the explanatory variables exhibited significant structural change with regard to our hypothesized submarkets. This may be caused by nonlinearity in the data; we expand our study of time on the market with Weibull duration models, presented in Exhibits 10 and 11.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

The coefficient results closely resemble the 2SLS results, and general discussion of these results is omitted. While the reader may wish to focus on significance from the model coefficients, Exhibit 10 also presents the marginal effects of the explanators in the four Weibull models.[21] As before, Oak Grove properties sell faster than non-*OakGrove* properties (7.6543 days faster than non-*OakGrove* properties), and the latitude (ln*Latitude*) (1.7264 days extra marketing time for each one minute of latitude north of the mean latitude line), brokerage (*NumBrokList*) (almost negligible marginal effect), and market (*PCList*) (a one unit increase in *PCList* decreases *DaysOnMarket* by approximately one week) effects hold as in the 2SLS outcomes. One notable addition is that larger properties (ln*SqFt*) exhibit longer marketing times in the combined sample. While the results are no stronger than in the 2SLS models, the Weibull results reinforce the 2SLS results in general.

Exhibit 10 | Weibull Duration Models—No Heterogeneity Correction
Dependent is *lnDaysOnMarket*

	Combined	PRE	PRE / POST	POST
Intercept	−194.5170**	−269.2675**	−101.6968	−127.0207
ln*Age*	−0.0730***	−0.0253	−0.0166	−0.0780**
	[−0.2376]	[−0.0681]	[−0.1165]	[−0.1475]
ln*SqFt*	0.4721**	0.2899	0.1514	0.3944
	[0.0137]	[0.0072]	[0.0080]	[0.0072]
ln*Bedrooms*	−0.1054	0.2582	−0.2802	−0.3688
	[−1.5437]	[3.3336]	[−7.5627]	[−3.2585]
ln*Bathrooms*	−0.0789	−0.0943	−0.0290	0.1241
	[−1.7368]	[−1.7272]	[−1.2096]	[1.7992]
OakGrove	−0.1501*	−0.0507	−0.1006	−0.2616
	[−7.6543]	[−2.2715]	[−10.088]	[−7.8266]
ln*Latitude*	58.1808**	84.2013**	34.8290	36.5663
	[1.7264]	[2.1046]	[1.9705]	[0.6679]
ln*Longitude*	−2.2241	−7.8199	−6.0777	1.4088
	[−0.1902]	[−0.5567]	[−0.9957]	[0.0748]
NumBrokList	−0.0008***	−0.0002	0.0000	−0.0014***
	[−0.0428]	[−0.0096]	[0.0011]	[−0.0465]
PCList	−0.1421***	−0.4144***	−0.2384***	−0.3671***
	[−7.2762]	[−15.5860]	[−22.3509]	[−10.446]
ln*ListPrice*	0.0754	−0.0100	0.0661	0.1303
	[0.0027]	[−0.0003]	[0.0042]	[0.0030]
N	1,090	407	279	404
p	1.0866***	1.4017***	1.8452***	0.9620***
Log-likelihood	−1,715.43	−535.95	−291.08	−682.09

Notes: Exhibit 10 presents the Weibull model with no heterogeneity correction. We model the time to sale for properties that sold using a survival function based on the Weibull distribution. The dependent variable is *lnDaysOnMarket*. Numbers in brackets are the marginal effects on *DaysOnMarket*. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCList* is the first principal component from the listing trend variables *List_ForeTrend, List_UnempTrend, List_TimeTrend,* and *List_IntTrend*. The brokerage effect (from *NumBrokList*) appears to persist in the Weibull model as it did in the 2SLS models. Market and trend variables (*PCList*) exhibit a significant effect on time on the market.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

Exhibit 11 | Weibull Duration Models—Heterogeneity Correction

	Combined	PRE	PRE / POST	POST
Intercept	−257.2476**	−443.1190**	142.5499	−68.2926
ln*Age*	−0.0722***	0.0017	−0.0648**	−0.0841
ln*SqFt*	0.3511	−0.0318	0.3366	0.2662
ln*Bedrooms*	0.0311	0.4471	−0.2648	−0.1775
ln*Bathrooms*	−0.1903	−0.0711	−0.2503	0.0135
OakGrove	−0.1252	0.0138	−0.3122**	−0.2475
ln*Latitude*	74.9626**	135.9231**	−36.4897	18.1657
ln*Longitude*	−0.7971	−9.4120	−6.4423	2.5834
NumBrokList	0.0007*	0.0011**	0.0007	0.0006
PCList	−0.1840***	−0.3931***	−0.4009***	−0.3724
ln*ListPrice*	0.2635	0.0841	0.1895	0.3144
N	1,090	407	279	404
p	0.8749***	1.0547***	1.3254***	0.8020***
θ	0.0098	0.0100	0.0010	0.010
Log-likelihood	−1,775.28	−570.34	−326.87	−704.64

Notes: Exhibit 11 presents the Weibull model with heterogeneity correction, meaning that the results presented in Exhibit 11 will be more reliable if latent heterogeneity is present in the data. *NumBrokList* is the number of listings taken by the listing brokerage firm during the study period. *PCList* is the first principal component from the listing trend variables *List_ForeTrend*, *List_UnempTrend*, *List_TimeTrend*, and *List_IntTrend*. θ is the heterogeneity parameter; the results shown here indicate that θ is not significantly different from zero at the 10% level, meaning that there is no significant heterogeneity present in our sample. Therefore, we refer to Exhibit 10 in the manuscript and provide no further discussion of Exhibit 11.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

Synthesis

Recall from the theoretical model of Forgey, Rutherford, and Springer (1996) that selling price and time-on-market are related to liquidity: $dL/dP^* > 0$ and $dL/dT < 0$.

In the discussion of empirical results, we demonstrated that, based on the results of *t*-tests and *F*-tests, the distribution of selling prices of properties in our sample increased as we moved from the first subgroup through the second subgroup to the third subgroup. Additionally, the results of the *t*-tests and *F*-tests for marketing time indicate that the average marketing time increased for the properties listed before Katrina but sold after Katrina as compared to the other two submarkets, while the variance of marketing times increased for the PRE/POST period but was shorter for properties sold in the POST submarket when compared to those sold in the PRE submarket. Taken together, we can infer that selling prices increased after Hurricane Katrina and that marketing times increased immediately after Katrina but decreased with time following Katrina to a level lower than the pre-Katrina level.

In context of Equations (4) and (5) and the Forgey, Rutherford, and Springer (1996) model, our empirical results suggest that Hurricane Katrina altered liquidity in the Hattiesburg residential real estate market, inducing an indeterminate change in liquidity immediately after the disaster that developed with time and actually surpassed the level of liquidity that existed prior to Katrina. This activity constitutes an overreaction in the market that was based on the flood of ‘‘bad news’’ information that immediately followed Katrina; this overreaction corrected itself in time as market participants gained a better perspective on the scope of the disaster's effects on the region.

Our results also suggest that there may have been a temporary shift in the market dynamics in this residential market. Along with the results of the 2SLS models and the Chow and Tiao-Goldberger tests, which indicate a structural change in pricing and time-on-market, we also observe the noted change in the Weibull duration dependence parameter *p*, which would suggest that the time-on-market dynamic changed as well.

Further, we present evidence that suggests that listing brokerage specialists—brokerage firms that listed more properties in the overall sample period—have a significant effect on selling price and time-on-market, obtaining higher selling prices in the PRE/POST submarket and shorter marketing periods in the POST submarket. This lends further insight into recent studies by Johnson, Zumpano, and Anderson (2007) and Salter, Johnson, and King (2008), which examine listing specialization in residential brokerage. It appears that listing specialists affected residential transactions in our sample area.

Conclusion

We present a direct test of the Forgey, Rutherford, and Springer (1996) model of liquidity within the context of an unforeseen information event, 2005's Hurricane Katrina. Using the methodology found in Allen, Springer, and Waller (1995) and Forgey, Rutherford, and Springer (1996), we examine Katrina's effect on the residential real estate market in Hattiesburg, Mississippi, vis-à-vis submarket effects. Empirical results from 2SLS pricing models and 2SLS and Weibull duration models suggest that the distributions of selling prices and marketing times changed due to Katrina and that these changes manifested themselves in the form of increased liquidity in the local market. Further, the structural relationship between selling price and physical property characteristics appears to have also changed during our study period, based on results from Chow and Tiao-Goldberger tests. Aside from increased liquidity, we also find that Katrina created a stark submarket effect, delineating properties that were both listed and sold pre-Katrina from those properties that were either listed pre-Katrina/sold post-Katrina or those properties that were both listed and sold post-Katrina. Additionally, we find a significant brokerage effect that became apparent post-Katrina.

These results provide evidence for the argument that residential real estate markets are informationally efficient, in that the market corrected for increased demand via increased selling prices (and associated increased marketing times) between our first and second submarket groups, and that prices and time-on-market adjusted downward in submarket period three as supply and demand stabilized. The resultant POST environment exhibits higher selling prices and shorter marketing times than were noted in the PRE submarket. This result, while intuitive, is important, given that the information event studied was unannounced. Future research may apply the chosen methodology to future unannounced events to test for efficiency in other residential real estate markets.

This manuscript investigates the effect of Hurricane Katrina on the liquidity of a residential real estate market located near the impact zone of that hurricane. We use existing theory and modeling techniques to model the market's liquidity, and we use existing statistical techniques to test the theory on a unique sample of properties drawn from a local MLS. Our results suggest that uncertainty in the residential real estate market caused an overreaction in terms of prices and marketing times but that this overreaction abated with time. The results indicate that in situations in which information flows quickly into a market, we may see an overreaction, though the market will correct. This correction is characteristic of a relatively efficient market.

Endnotes

1 Bush Sees Long Recovery for New Orleans; 30,000 Troops in Largest U.S. Relief Effort. *The New York Times*, September 1, 2005, sec. A, col. 6, p. 1.

2 Rutherford, Springer, and Yavas (2005) present evidence that agents who sell their own properties glean higher prices for those properties.

3 See Guntermann (1995), Colwell and Scheu (1998), Isakson (2004), Uyar and Brown (2005), Musil (2007), and Smith (2008) for suggestions regarding the impact of these types of factors on property values.

4 U.S. Bureau of the Census, www.census.gov.

5 Coast is Home. *Mississippi Sun Herald*, June 11, 2006, online edition, www.sunherald.com.

6 Morgan (2007) addresses the impact of Hurricane Ivan on a Northwest Florida community; however, our analysis differs significantly from that employed by Morgan.

7 For an alternative presentation of submarket methodology, see Berry, McGreal, Stevenson, Young, and Webb (2003).

[8] This timeframe allows an equal number of calendar days prior to and after Hurricane Katrina.

[9] While our discussion focuses on variables and their natural logarithmic transformations, we use other affine transformations of variables in addition to natural logs to ensure proper model fit.

[10] Both logged and unlogged versions of primary variables, such as *SoldPrice* and *DaysOnMarket*, are employed in our analysis without further explanation.

[11] Specifically, Oak Grove High School received ''Level 5—Superior'' performance scores from the Mississippi Department of Education, while Hattiesburg High School received ''Level 3—Successful'' performance scores (source: Mississippi Department of Education, www.mde.k12.ms.us).

[12] We also attempted to include dummy variables that control for seasonal effects related to the month in which the property listed (*List_Spring*, *List_Summer*, *List_Fall*, and *List_Winter*) and sold (*Sold_Spring*, *Sold_Summer*, *Sold_Fall*, and *Sold_Winter*). As in Forgey, Rutherford, and Springer (1996), Winter is defined as January, February, and March; Spring is defined as April, May, and June, etc. However, these introduced serious collinearity, and we chose to include only the time trend variable to account for changes in time. In essence, the seasonal dummies were confounded by the study's design; for example, in the PRE submarket, 48.68% of the properties were listed in the Winter, 44.30% were listed in the Spring, 7.02% were listed in the Summer, and 0% were listed in the Fall. In the PRE/POST submarket, 9.79% of properties were listed in the Winter, 35.01% listed in the Spring, 55.20% listed in the Summer, and 0% listed in the Fall. In the POST sample, 33.26% listed in the Winter, 1.32% listed in the Spring, 17.18% listed in Summer, and 48.24% listed in the Fall. Hence, Winter is highly correlated with the PRE submarket, Summer is highly correlated with the PRE/POST submarket, and the Fall season is highly correlated with the POST submarket; bias is introduced.

[13] We extend our thanks to an anonymous referee who suggested additions to our original model, which was much more parsimonious.

[14] In actuality, we performed the *F*-tests first to ensure that the proper *t*-tests (i.e., assuming unequal variances) were performed.

[15] In general, the VIF values for these variables range from 10 to 50. An examination of the condition numbers from a Principal Components Analysis (PCA) reveals that all explanatory variables have condition numbers greater than 10, the upper bound for coefficient reliability suggested by Belsley, Kuh, and Welsch (1980).

[16] An alternative to the PCA approach used here would be to include only the trend variables with Eigenvalues larger than the mean Eigenvalue for the four trend variables in our estimation. In practice, this would have meant discarding the interest rate variable, the unemployment variable, and the foreclosure variable in favor of the time trend. Since this would have reduced both our model's information content and the interpretability of the discarded factors (as they would have not been estimated), we chose the present approach.

[17] VIFs, which are unreported, have values less than 5.00 for all variables in all models.

[18] In Exhibit 3.1, the marginal effects are calculated for a 1% increase in the underlying rate in period -1, as defined when constructing the trend variables. The exception is *List_TimeTrend*, with marginal effect calculated based on a one-period increase in time. Exhibit 7.1 is calculated in a similar manner.

[19] Using ln*SoldPrice* as the instrument introduced significant collinearity problems into our model. The list price is undoubtedly related to the selling price, though not perfectly so.

[20] The marginal effect is the effect on *DaysOnMarket* caused by a one-unit change in the factor underlying the trend holding the other three factors constant; for example, a 1% increase in the prime rate, a 1% increase in the unemployment rate, a 1% increase in the foreclosure rate, or a one period increase in time. Changes in underlying factors are calculated from the mean values.

[21] The marginal effects are generally calculated as the effect of a one-unit change (from the mean) in a given (underlying) variable on *DaysOnMarket* (the result is a number of days). For example, we examine the effect on *DaysOnMarket* if we increase the number of bedrooms from the mean value to the mean value plus one bedroom. There are, however, a few exceptions. Marginal effects of *OakGrove* are calculated as the change from *OakGrove* = 0 to *OakGrove* = 1. Marginal effects of latitude and longitude are a one-minute increase in latitude or longitude.

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