Media on Short-Term House Price Dynamics*

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Abstract

The residential housing market is dominated by households that are often inefficient at processing information. This paper presents evidence that the media play an information-providing role that affects short-term housing price dynamics. Large volume of housing news can create differing views on the housing market among households. Coupled with shorting constraint in the housing market, differing views on the housing market leads to short-term increase in house prices. I provide evidence for this hypothesis in two ways. I first provide evidence using plausibly exogenous variation on housing news around FOMC meeting dates, media can causally affect households' home-buying decisions. Secondly, I show using county-level panel time-series regression that increase in housing news is associated with 7-10 bp (annualized) housing return over the next 4 to 6 months.

Keywords: Short-term House Price Movement, Media, Information

JEL classification: D10, G11

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I. Introduction

The housing market is a significant part of the economy. Over two thirds of households[1] in the US own homes, and despite the benefits of diversification, houses remain an overwhelming portion of households' portfolios (Tracy, Schneider, and Chan, 1999; Nakajima et al., 2011). As such, understanding the dynamics of house price movements can have significant welfare implications. In this paper, I provide evidence, which suggests media can substantially affect the movement of housing prices in the short term.

Evidence from behavioral economics and other streams of literature indicate that people can be affected by the media. Examples include the impact of newspaper articles on stock prices (Huberman and Regev, 2001; Liu, Smith, and Syed, 1990), the impact of mass media on politics (Graber, 2009), and the impact of media on violence in society (Anderson and Bushman, 2002). In the finance literature, while behavioral biases have been documented among institutional investors (Bailey, Kumar, and Ng, 2011), it is more accepted that households exhibit behavioral biases and are influenced by the media (Barber and Odean, 2011)[2].

In contrast to other financial markets, the residential housing market is dominated by households. According to a 2013 Federal Reserve report, Atlanta had the highest institutional investor activity in 2012 among Metropolitan Statistical Areas (MSAs) at a mere 16%[3], which suggests that the remaining 84% of the activity can be attributed to households. Given households' responsiveness to the media and their dominance in the housing market, I hypothesize that the media play an important role in households' home buying decisions and, in turn, the housing market.

The model is as follows. Due to the high cost of information processing and limited attention, households can process only a fixed amount of news, which affects their expectations about the future housing market. For instance, if each piece of news is either positive or negative with some distribution and news articles are sampled without replacement, the probability of obtaining a disproportional (mostly positive or mostly negative) combined signal increases as the number

[1]In this chapter, I use "individuals" and "households" to mean the same thing.

[2]The media may affect households' behavior by providing them with information (a rational story) or through other means (a behavioral story). I assume that if a household's behavior changes after receiving a piece of news, it is because of the news and not because of how it is presented. However, both mechanisms lead to the same empirical results, and hence I do not distinguish between these stories.

[3]For more details, please see `https://www.federalreserve.gov/econresdata/notes/feds-notes/2013/business-investor-activity-in-the-single-family-housing-market-20131205.html`

of news articles increases. Increased disproportional combined signal creates more heterogeneous beliefs about the housing market and increases the number of households that want to buy or sell. However, because of shorting constraints[4], only households that currently own a home are able to react to a negative signal, whereas both homeowners (investing in a second home or moving into a bigger home) and non-owners can react to a positive signal. This asymmetry results in a positive relationship between housing news intensity and the subsequent housing return. Further details of the model are outlined in Section II.

The role of shorting constraints in the presence of heterogeneous beliefs has received a great deal of attention in the finance literature (Harrison and Kreps, 1978; Diamond and Verrecchia, 1987). Although earlier studies focus on the equity market, recent studies highlight shorting constraints as an important feature in the housing market (Nathanson and Zwick, 2014; Burnside, Eichenbaum, and Rebelo, 2016; Favara and Song, 2014). Heterogeneous beliefs can originate from various sources, such as the different weights used on past realization extrapolation (Granziera and Kozicki, 2015) and different experiences in the housing market (Kuchler, Zafar, et al., 2015). Similarly, Bailey, Cao, Kuchler, and Stroebel (2016) finds that social media play an important role in the housing market. My findings are consistent with these studies, and I argue that the media are a source of news shocks that create heterogeneous beliefs among households.

Due to the importance of the housing market as a research question, the relevant literature is too diverse to fully represent here. Hence, only the studies deemed most relevant to this study are highlighted. One of the more relevant streams of literature about the housing market is time-series dynamics. House prices are known to exhibit short-term momentum and long-term reversal. Recent attempts to explain these phenomena include concave demand functions[5], which motivates sellers to move prices slowly (Guren, 2014) and leads to the existence of momentum traders (Piazzesi and Schneider, 2009).

More germane to this study may be the literature on cross-sectional dynamics. These studies consider why housing prices in certain areas move differently from prices in other areas. One possible approach is risk-based stories, or cross-sectional asset pricing. Cross-sectional asset pricing,

[4]There are several ways to short the housing market, including shorting the stocks of real-estate companies such as REITS and selling CME Case-Shiller futures. Yet these strategies at best give negative exposure to MSA-wide housing risks for major MSAs, and hence cannot be used to exploit the county-level local effects documented here.

[5]Guren (2014) defines a concave demand function as a demand function that decreases more with a small price increase than it increases with the same sized price decrease.

which gained popularity through a series of papers by Fama and French (Fama and French, 1992, 1993), argues that differences in exposure to risk factors can explain cross-sectional differences. Cross-sectional housing asset pricing studies, which are relatively more recent (Cannon, Miller, and Pandher, 2006; Case, Cotter, and Gabriel, 2011), explain a significant proportion of heterogeneity in housing returns across US MSAs. However, as suggested by Ling, Ooi, and Le (2015), there are limits to the extent to which risk-based stories using publicly available data can explain cross-sectional house price dynamics. For example, Soo (2013) shows that fundamentals that explain nearly 70% of house price variations in 1987-2000 explain only 10% of the variation in the 2000s.

Other approaches to cross-sectional dynamics focus on the specific characteristics of different regions. For example, Glaeser, Gyourko, and Saks (2005) argues that differences in the difficulty of obtaining building permits explain why certain cities experience high home price appreciation. Gyourko, Mayer, and Sinai (2013) argues that a limited housing supply combined with differences in income distribution explains house price differences across regions. Although related to this literature, this study is unique in that it focuses on short-term dynamics. I offer evidence of a short-term (less than a year) correlation between the media and housing returns, which is consistent with an informational story. Whether this informational story has a long-term effect is an interesting question, but it is beyond the scope of this study.

Another body of relevant literature concerns the role of media, which has received a great deal of attention in academia. Even within the finance literature, many studies document the predictive power of media. Perhaps the most influential such work is Tetlock (2007), which uses text mining to analyze a *Wall Street Journal* column, "Abreast of the Market." Tetlock argues that a sentiment index created from the column can predict the Dow Jones Index. In line with Tetlock (2007), the predominant interpretation of media's role is the reflection of market sentiment, and numerous studies document the impact of sentiment on the stock market (Edmans, Garcia, and Norli, 2007; Baker, Wurgler, and Yuan, 2012; Brown and Cliff, 2005).

To the best of my knowledge, the only study that links the media to the housing market is Soo (2013). Soo analyzes housing articles from a major newspaper in each of 20 MSAs using text mining to build a sentiment index. Soo argues that newspaper articles contain information about the housing market that is beyond fundamentals, which is useful for forecasting housing prices at a horizon of one to three years.

This study argues that the media have an influential role on households' home-buying decisions, which in turn affects short-term housing price dynamics. As such, I start off with providing an evidence, which suggests the media causally affects mortgage applications, which proxies households' home-buying interest. This is done through using plausibly exogenous variation in housing news predicted by FOMC meetings. Afterwards, this study uses county-level housing prices and newspaper data to document local media's predictive power on local house prices at the 4 - 6 month horizon, which is consistent with media affecting house prices through households' home-buying decisions. Using data from 269 counties, I find that the increase[6] in the media's housing content leads to a 8-10 bp (annualized) increase in local housing returns after 4-6 months. To the best of my knowledge, this is the first study to document short-term correlation between media and the housing market and to offer any causal evidence on the relationship between media and the housing market.

This chapter proceeds as follows. In Section II, I briefly describe the mechanism through which I hypothesize how the media affects housing prices. In Section III, I describe the data sources and analysis sample. In Section IV, I discuss the causal relationship between housing media and households' mortgage applications. In Section V, I document the short-term predictive power of local media on local housing returns. Section VI concludes the chapter.

II. Model

In this section, I present a simple model that illustrates the mechanism through which the media affects the housing market. In this model, households obtain different news about the housing market because of inefficiencies in processing information. Furthermore, the likelihood of a disproportionate combined signal increases as the amount of news increases because households can process only a small proportion of the news. Although both homeowners and non-owners receive news shocks, due to shorting constraints, only current homeowners can react to negative news shocks. Hence, an increase in housing articles increases housing demand (from both current owners

[6] The coverage level of housing news varies greatly across counties in my data sample. As I observe housing news only intermittently in many counties, my independent variable is the direction of the housing news level change rather than the magnitude change.

wanting a second home and non-owners) more than the housing supply (only from current owners)[7]. The number of housing articles is positively correlated with subsequent housing prices and returns. The essence of the mechanism—namely, shorting constraints and heterogeneous beliefs—is similar to mechanisms explored by other studies (Favara and Song, 2014). The source of heterogeneous beliefs is unique to this chapter.

Consider a two-period economy ($t = 0, 1, 2$) with only two investment instruments: zero-coupon bonds and housing. This assumption is motivated by the observation that while a large number of households are homeowners, only a small portion of households own stocks. In this economy, there is a mass 1 of agents whose goal is to maximize their wealth, and $0 < \mu < 1$ of these agents currently own one house. Assume there are many rental facilities that provide rental housing at a rate of c^r each period for agents without a house. There are no transaction costs associated with buying or selling a house, and each house is assumed to be identical and hence to have the same price. Each agent is initially endowed with wealth W, which is sufficient to buy a house. An agent without a house can decide whether to buy a house, and an agent with a house can decide to sell his, do nothing, or buy an additional house to rent out.

The goal of each agent is to maximize his wealth at $t = 2$. At $t = 0$, each agent obtains news about the housing market, $\eta \sim N(m, n^2)$, which affects his expectation of home prices at $t = 2$, where n represents the number of housing news articles in the media. Each agent knows the setup of the economy but does not know the realization of η for other agents.

The rationale for more housing news leading to more belief dispersion is as follows. Assuming that additional news is equally likely to be positive or negative, if agents have limited attention and they sample news from the media without replacement, it is more likely that agents will receive disproportionate combined signals when there is more news. For example, when there are three pieces of positive news and three pieces of negative news, digesting only two of them yields a $1/5 = 20\%$ chance of getting strong news (i.e. both are positive news) about the housing market. However, when there are six pieces of positive news and six pieces of negative news, this chance increases to $5/22 \approx 22.7\%$. If only positive or negative news increases, the actual distribution can

[7] In the real world, the housing supply may vary with external factors such as new construction. However, external housing supply factors tend to be more inelastic. For example, it takes on average 6 months for new homes to be built according to the *Wall Street Journal* (`http://www.wsj.com/articles/average-time-to-build-a-house-6-months-1420652311`). I focus on the short-term effect of local media on housing prices and ignore external factors.

be skewed; however, for simplicity, I assume that a disproportionate increase in positive or negative news only affects the distribution of η through m and n.

Based on the news at $t = 0$, each agent makes a decision to buy or sell a house at $t = 1$. Each agent can deduce the market clearing price P_1 based on the distribution of η; hence, the optimization problem for non-owners is

$$\max \begin{cases} W - c^r - P_1 - c^o + \mathbb{E}_1[P_2] & : \text{Buy} \\ W - 2c^r & : \text{Not Buy} \end{cases}$$

If the agent decides to buy a home in period 1, he or she pays rent of c^r at $t = 0$, as he or she is without a home, and pays the price of the home P_1 and a maintenance cost of c^o at $t = 1$. At $t = 2$, he or she gets the price of the home at the time. If he or she decides not to buy a home, then his or her final wealth is his or her initial wealth less two periods' rent.

For agents endowed with homes, the optimization problem is

$$\max \begin{cases} W - c^o - P_1 - 2c^o + c^r + 2\mathbb{E}_1[P_2] & : \text{Buy} \\ W - 2c^o + \mathbb{E}_1[P_2] & : \text{Do Nothing} \\ W - c^o + P_1 - c^r & : \text{Sell} \end{cases}$$

Similarly as before, if an agent with a home decides to buy another, then at $t = 0$, he or she pays the maintenance cost; at $t = 1$, he or she pays the price of the home and the maintenance costs of two homes and gains rent from one of them; and at $t = 2$, he or she gets the price of the home at the time.

As discussed previously, each agent's future expectation of the home price is determined by a fundamental value and news shock. Assume that the fundamental value of a home v is determined by economic factors that do not change in the timeframe of the model. Hence,

$$\mathbb{E}_1[P_2] = v + \eta, \eta \sim N(m, n^2)$$

Lastly, assume that because of unforeseen activities such as job relocation, there is also a probability λ that an agent has to relocate. The shock will come at $t = 0$, and for agents with homes, this will mean that they have to sell at $t = 1$. This relocation shock is independent from the news shock. The relocation shock is introduced to model the relatively inelastic supply but is not crucial for the result. Although not modeled here, the inelastic supply can also be attributed to households' loss aversion, as discussed in (Genesove and Mayer, 2001).

Consider the perspective of an agent without a house. He or she will decide to buy a house if

$$
\begin{aligned}
W - c^r - P_1 - c^o + \mathbb{E}_1[P_2] &> W - 2c^r \\
&\implies \eta > P_1 - c^r + c^o - v
\end{aligned}
$$

The problem for an agent with a house is similar. He or she will decide to buy an additional house if $\eta > P_1 - c^r + c^o - v_0$, sell his or her house if $\eta < P_1 - c^r + c^o - v_0$, and be indifferent if equality holds.

Given the normal distribution of the news shock η and that the λ of individuals with a high news shock will not be able to participate because of relocation, the demand function as a function of the $t = 1$ home price P_1 is

$$D(P_1) = (1 - \lambda)\left(1 - \Phi\left(\frac{P_1 - c^r + c^o - v - m}{n}\right)\right)$$

The supply function can be similarly computed.

$$S(P_1) = \underbrace{\mu\lambda}_{\text{Supply from Relocation Shocked Owners}} + \underbrace{\mu(1-\lambda)\Phi(A)}_{\text{Supply from Non-Shocked Owners}}$$

where, $A = (P_1 - c^r + c^o - v - m)/n$

Equating the supply and demand yields the housing price P_1 as a function of amount of housing news in the media n.

$$P_1 = n\Phi^{-1}\left(\frac{(1-\lambda)(1+\mu) - \mu}{(1-\lambda)(1+\mu)}\right) + v + c^r - c^0 + m \tag{1}$$

Equation 1 gives a positive relationship between the amount of housing news and housing prices when $((1-\lambda)(1+\mu) - \mu) \,/\, ((1-\lambda)(1+\mu)) > 1/2$. Using reasonable assumptions about μ and λ, such as the percentage of homeowners $\mu = 0.65$ and relocation rate $\lambda = 0.12$, provides this result[8].

[8] According to the US Census, the US mover rate has remained stable at 12% since 2008. Similarly, according to

Based on equation 1, it can be deduced that housing returns are positively correlated with changes in the housing returns. Namely,

$$\Delta P_1 = \Phi^{-1}\left(\frac{(1-\lambda)(1+\mu)-\mu}{(1-\lambda)(1+\mu)}\right)\Delta n$$

III. Data

For this study, I obtain data from multiple sources. Perhaps the most important data in this study are newspaper articles, which are sourced from NewsBank's Access World News (AWN) database, provides news articles for various media types from 1978 onward. Although there are two other major newspaper databases, Factiva and LexisNexis, AWN is the only database that provides comprehensive newspaper articles from local newspapers[9]. AWN has data on 863 US newspapers[10]. It contains all articles from newspapers with the exception of advertisements and articles by syndicated columnists and freelance writers. I focus on newspapers as a proxy for the media, which may include radio, television, magazines, etc. Although AWN does not include a comprehensive set of newspapers in circulation in the US, I assume that the articles included in the database are unbiased in their representation of the local media news flow.

Housing articles are extracted from the database using the keywords "housing market" and "housing price". The keywords "housing," "market," and "price" all had to be included in either the body or the headline for an article to be included in my sample. I limit the sample to articles from newspapers (i.e., I exclude articles from magazines, journals, and Web-only sources). I also drop articles from non-English-language newspapers. Figure 1 shows a screenshot from AWN.

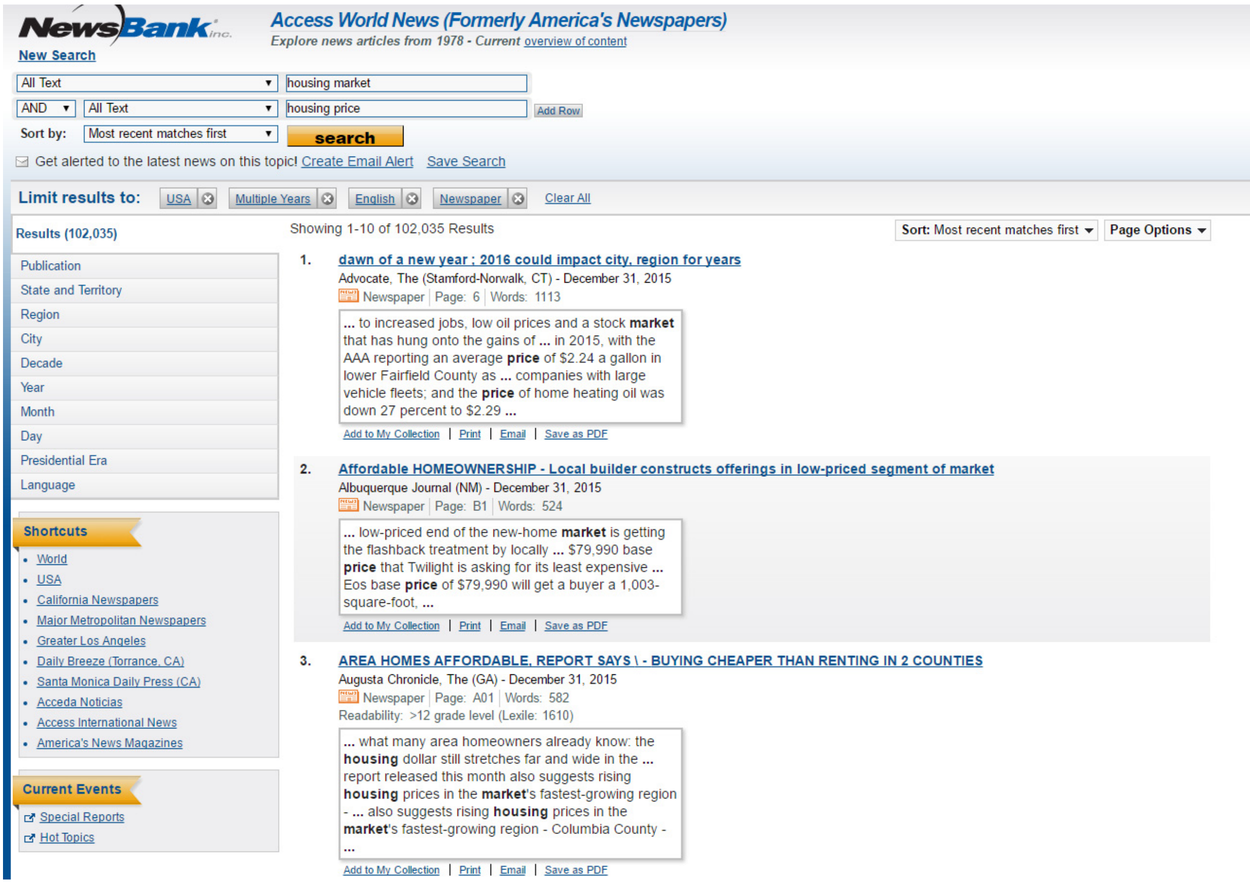
I obtain 210,964 articles published between 1998 and 2015 from 744 newspapers. These newspapers come from 447 counties. Figure 2 plots the counties represented in the newspapers from AWN during my sample period of 1998-2015. As shown in Figure 2, the database covers most major counties throughout the US. While some counties are part of large cities with more than five newspapers, such as Los Angeles, San Francisco, Chicago, Philadelphia, Boston, and New York

the US Census, homeownership in the US was 62-68% in 2008-2015.

[9]I assume that local housing market-related news is best represented in local newspapers or in newspapers that are headquartered locally. Furthermore, it is likely that households are most receptive to local newspapers. As such, I use local newspapers to represent the media's effect on households.

[10]at the time of access

Figure 1. NewsBank Screenshot



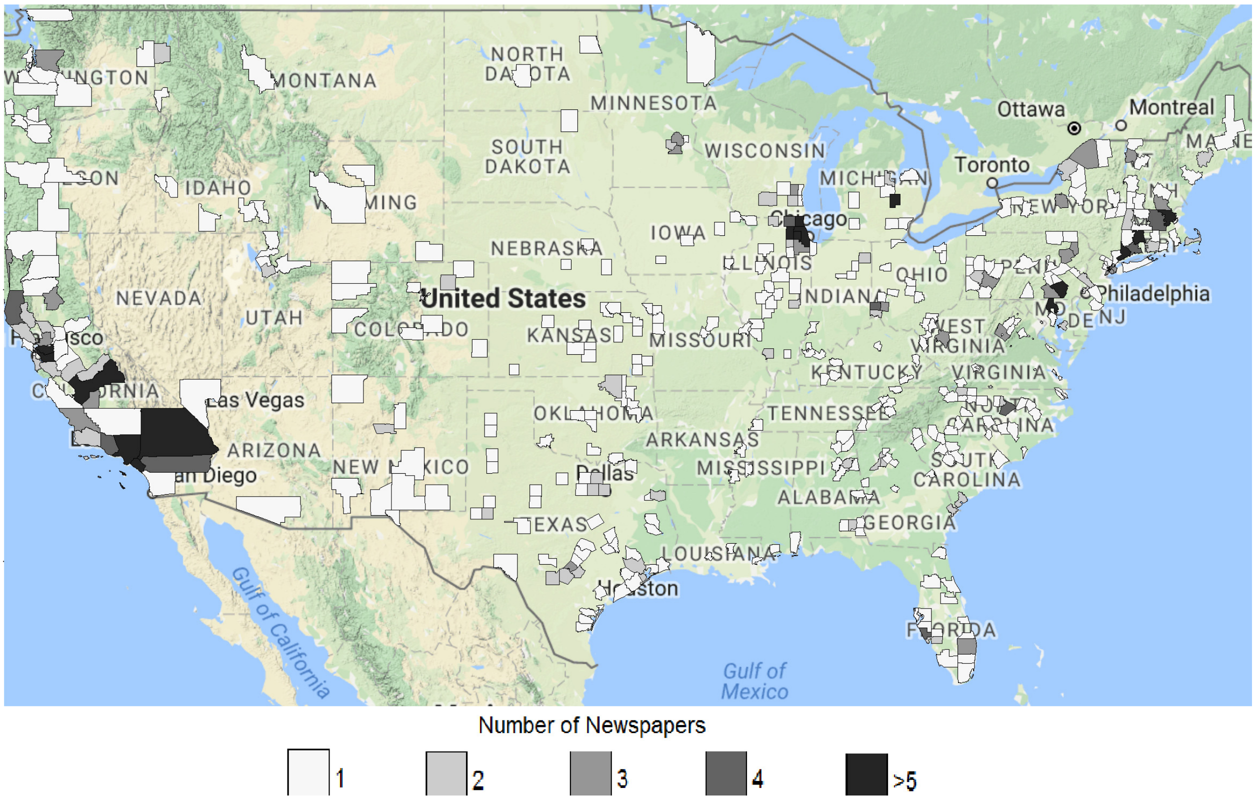
Notes: This figure shows a screenshot of the NewsBank database

(shaded black), the vast majority of the counties in the sample have only one newspaper.

AWN provides the town or city in which the newspaper is located. As mentioned previously, I assume that each newspaper provides news that is representative of the local media at the time. As my unit of analysis is the county, I assume each newspaper represents the media of the county. Each town or city is matched to the county via the county or counties listed on the town or city's Wikipedia page. For certain towns or cities located at the borders of multiple counties, I include the newspaper for all of the counties. Hence, some newspapers are counted in multiple counties. When there are different titled newspapers circulated by the same company (e.g., Daily vs. Sunday), I assume them to be the same newspaper.

The housing data are obtained from Zillow, as it is currently the only source of public data on county-level monthly house price indices. The data are updated with a 18-23 day lag every month.

Figure 2. Counties Covered by NewsBank



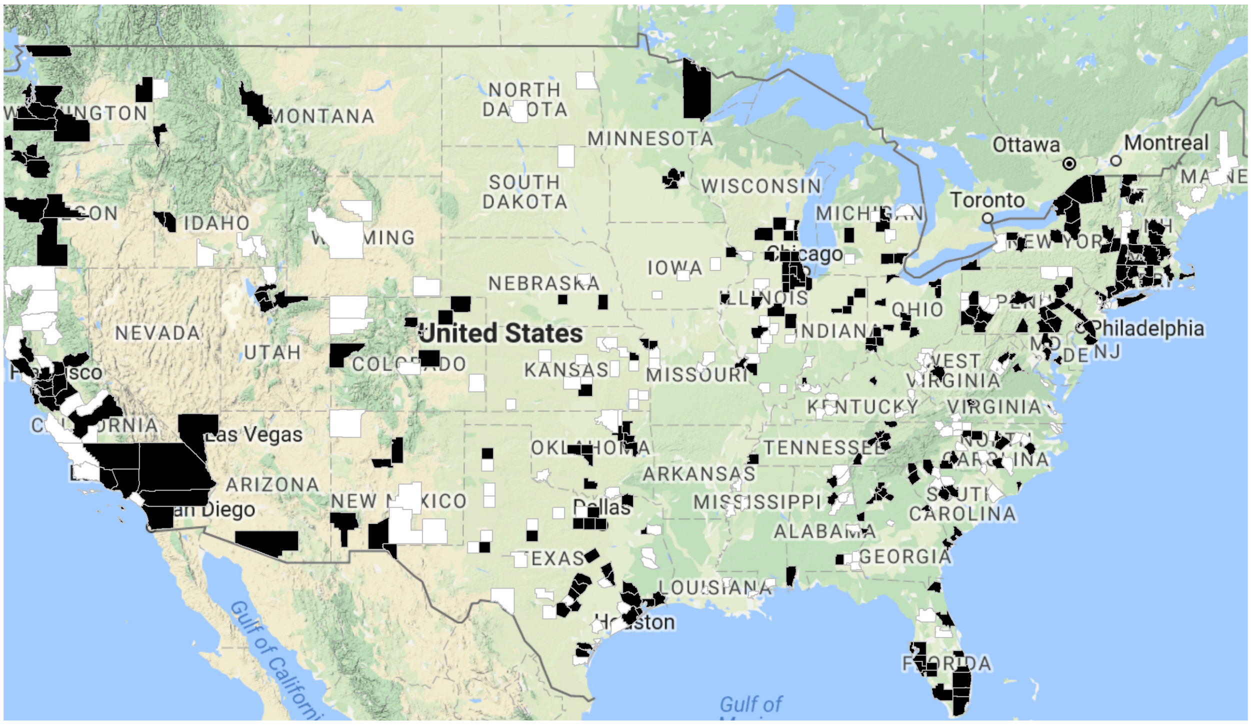
Notes: This map plots all of the counties with newspapers covered in the NewsBank database. The white shade indicates that NewsBank includes only one newspaper from the county, whereas the black shade indicates that NewsBank includes more than five. Not shown in the plot are four counties in Alaska and one county in Hawaii.

Zillow's HPI methodology differs from commonly used HPIs such as S&P Case-Shiller in several ways. Perhaps most importantly, S&P Case-Shiller is based on repeat sales, meaning that only houses that have been sold multiple times are included. The price change between the two or more transactions are aggregated using the weighted average to obtain the S&P Case-Shiller HPI. The Zillow HPI takes a fundamentally different approach in that it uses the Z-estimate, an estimated value of a home based on its proprietary machine learning algorithm.

Zillow's Z-estimate uses multiple sources of data, including prior sales, county records, tax assessments, real estate listings, mortgage information, and GIS data. Furthermore, Zillow's website allows homeowners to view the entire history of Z-estimates and to report home improvements, which would otherwise take a long time to appear in official records. The Zillow HPI is the median of the Z-estimates of all of the homes in a region. Thus, the Zillow HPI represents 95% of the US housing stock by market value, while S&P Case-Shiller represents 71%. Other differences include that whereas S&P Case-Shiller uses foreclosed sales data, Zillow does not[11].

Zillow HPI is relatively new compared with S&P Case-Shiller, as the company was founded in 2006 and the current Z-estimate valuation model was released in June 2011. Hence, the Zillow HPI is not as established as S&P Case-Shiller in the finance literature. However, Zillow is the largest online real-estate database company and has the 30th highest traffic in the US[12] As such, Z-estimates receive extensive scrutiny and are unlikely to be significantly biased.

Figure 3. Counties Analyzed



Notes: Black-shaded counties have both housing and newspaper data and are thus included in the analysis. The white-shaded counties are included in NewsBank but lack housing data. Four counties in Alaska and one in Hawaii are also included in the analysis.

Due to the constraints on the Zillow house price data, after matching the housing price data with the newspaper data, I obtain a sample of 269 counties with complete data between January 1998 and December 2015. During the analysis, I drop the January 1998 observations to compute changes in the media's housing content. Figure 3 plots the counties with data on both housing

[11] Zillow argues that this makes their HPI more accurate because foreclosure sales do not accurately represent health home transactions.
[12] As reported by Similar Web on August 2016.

prices and media that are included in the analysis. The counties shaded in black are included, while the counties shaded in white are excluded because of a lack of housing price data.

Figures 4a and b plot the total number of housing-related news articles over time for different cities and the average HPI of counties that are part of the city. As different counties of the same MSA may have HPIs on different scales, each county's HPI is divided by the whole sample average before averaging. The plots are for 18 major MSAs[13]. In each plot, the black line represents the total number of housing articles (scale on the left). The grey line represents the average HPI for counties in the MSA (scale on the right). There appears to be some contemporaneous movement between the two lines, especially during the crisis period. However, whether one leads the other is not immediately clear from the figures.

Figure 5 plots the total number of housing-related news articles across all counties and the proportion of news that is positive. Each housing article is sorted into positive, negative, and unclassified bins through the algorithm described in Section B. The proportion of positive news is computed as the number of positive news articles divided by sum of positive and negative news. According to this classification, excluding the housing crisis, the proportion of positive news is relatively stable at around 60%.

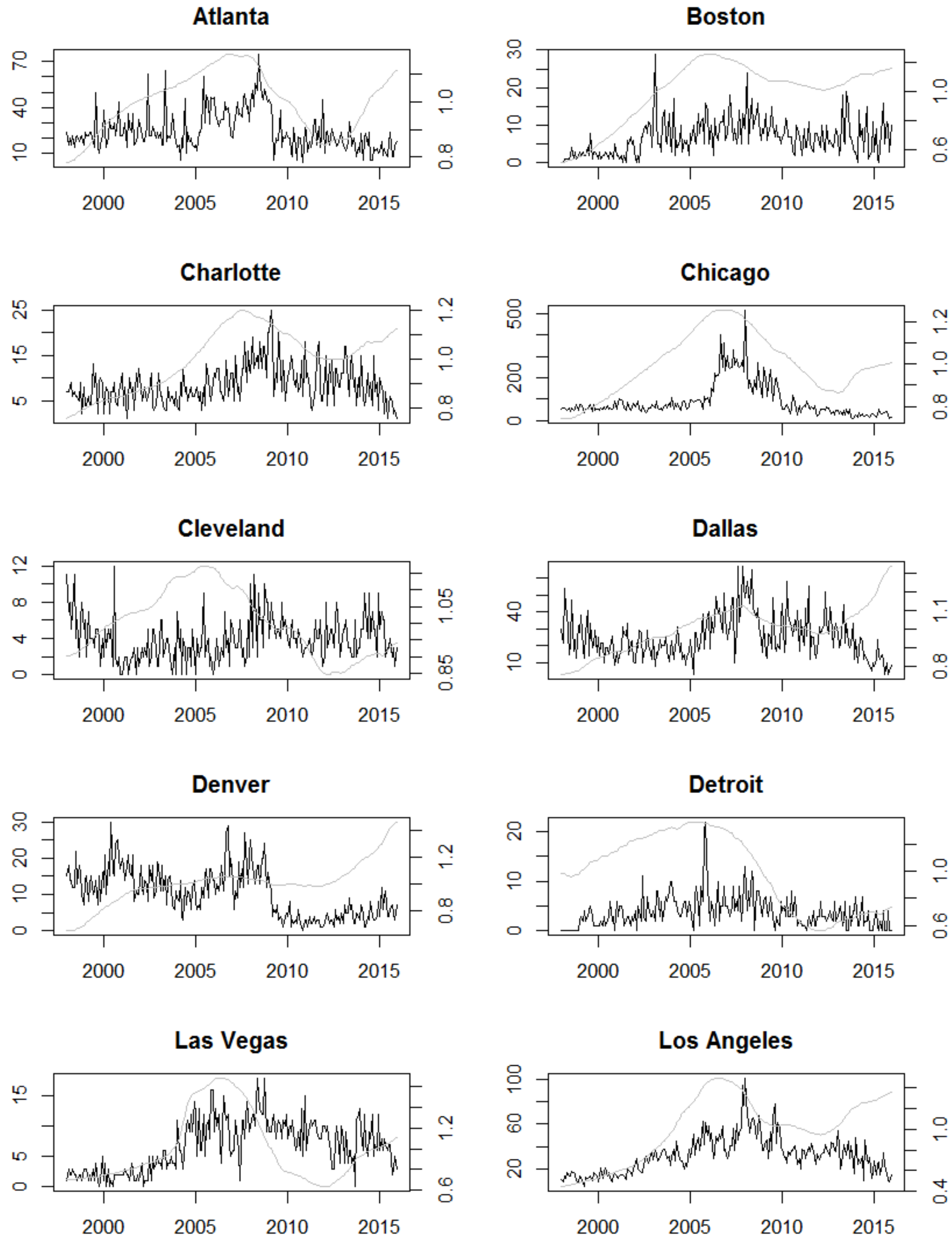
For a measure of weekly mortgage applications, I use Mortgage Bankers Association (MBA) U.S. Purchase Index. MBA's weekly application survey, which dates back to 1990, "captures more than 75 percent of all retail and consumer-direct channel application volume."[14] The U.S. Purchase index is based on this survey and represents the volume of all mortgage applications for single family home purchases. Each week (Saturday to Friday), number of mortgage application is captured through survey and the total volume is normalized so that the week of March 16th 1990 gets index level of 100. The U.S. Purchase Index during my sample period is presented in Figure 6

Other data sources are included in Table 1

[13] These are 20 counties that are part of the S&P Case-Shiller 20-City Composite index. Phoenix and DC are excluded because of a lack of newspaper or housing price data.

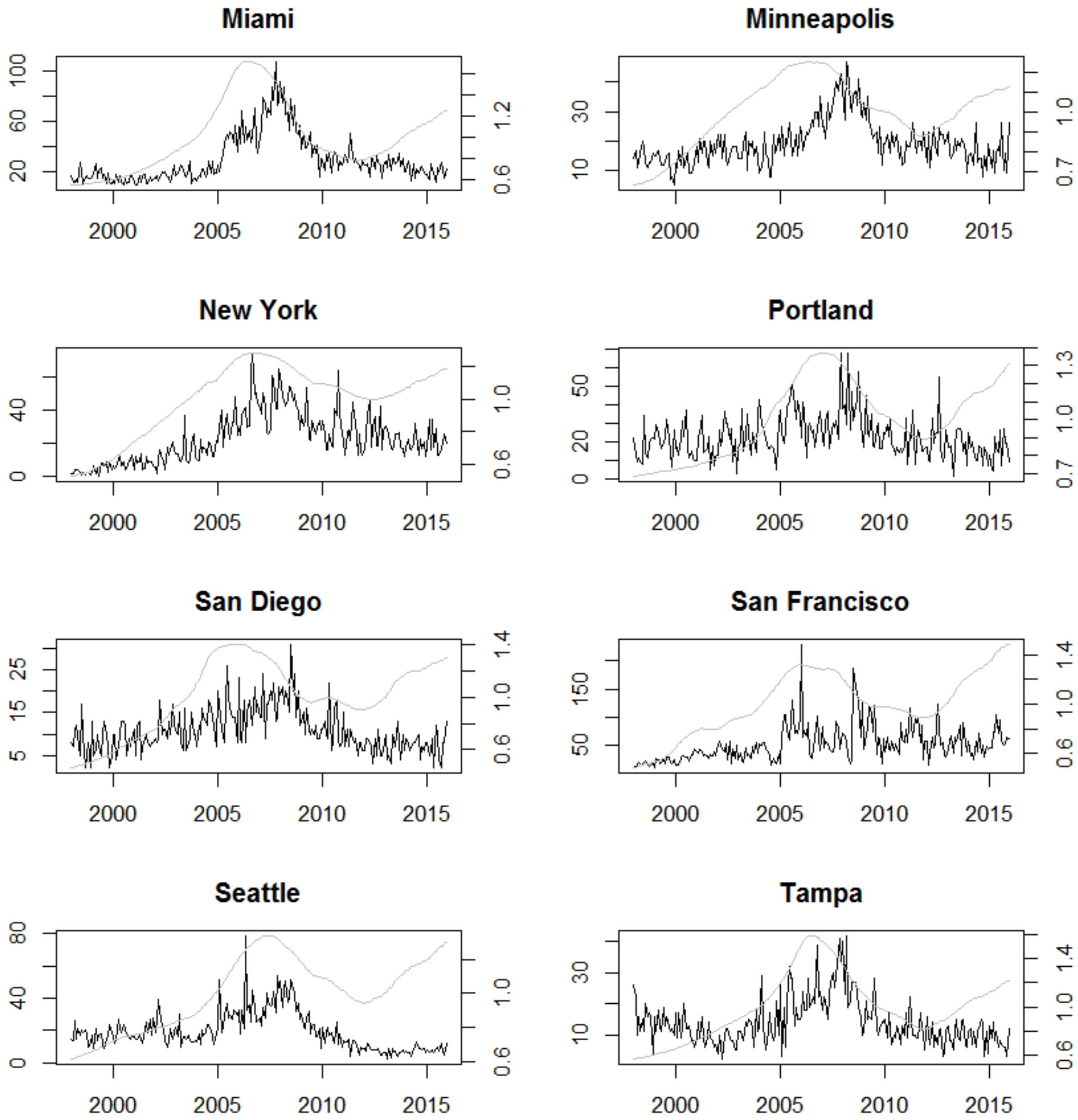
[14] MBA Weekly Application Survey `http://apps.mba.org/files/Research/HistoricalWAS/WASMethodology.pdf`

Figure 4a. Housing Articles and Housing Return



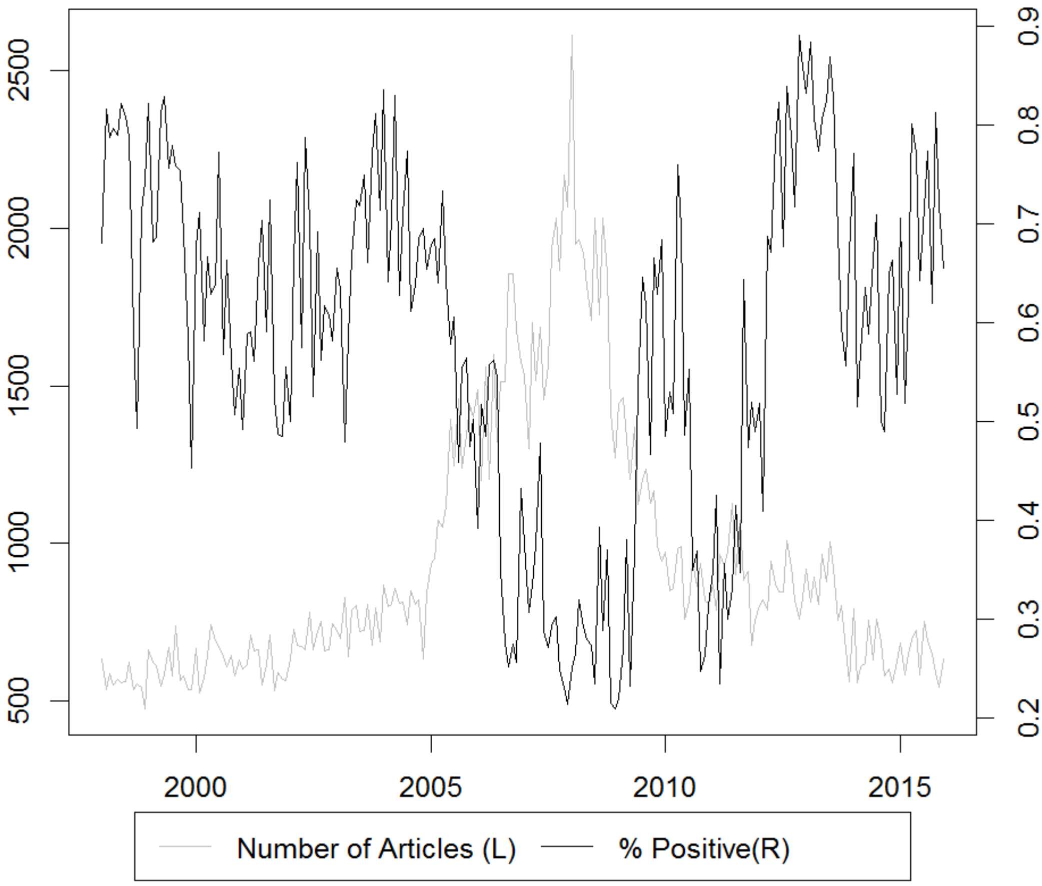
Notes: These figures plot the total number of housing articles in each city (black) and the average HPI (grey). The average HPI is computed by averaging the demeaned county-level HPIs. The total number of articles uses the left scale and the average HPI uses the right scale

Figure 4b. Housing Articles and Housing Returns



Notes: These figures plot the total number of housing articles in each city (black) and the average HPI (grey). The average HPI is computed by averaging the demeaned county-level HPIs. The total number of articles uses the left scale and the average HPI uses the right scale

Figure 5. Average Normalized Articles and Proportion of Positive/Negative Articles

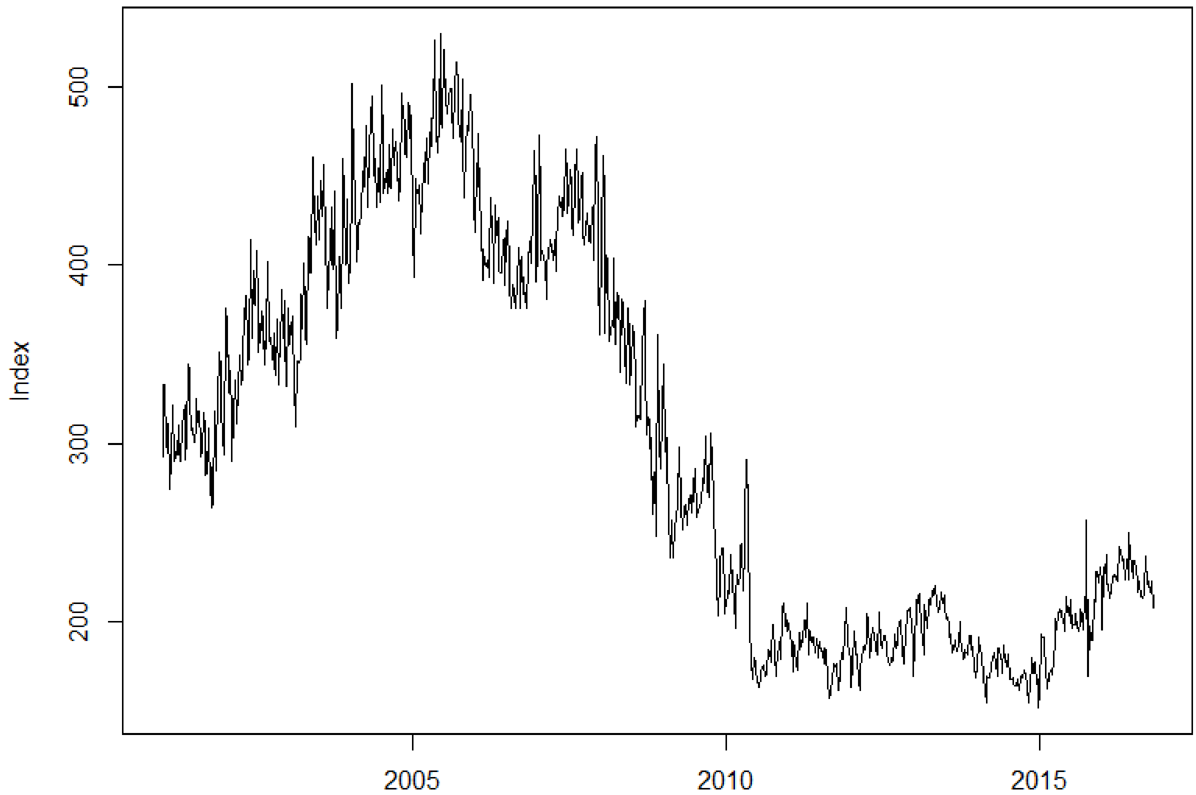


Notes: This figure plots the total number of housing articles in the data (grey) and the proportion of news that is positive (black). The number of articles has the scale on the left, and the proportion of positive articles has the scale on the right (%)

IV. Media on Mortgage Applications

In this section, I present evidence, which suggests that the media affects households' decision to buy homes. I show this through documenting correlation between plausibly exogenous variation in news article count and subsequent mortgage applications. The analysis is conducted through instrumental variable (IV) and Two Stage Least Squares (2SLS) analysis with FOMC meeting dates as the instrument. I will first describe the identification strategy using FOMC meeting dates and discuss the results of the analysis.

Figure 6. MBA U.S. Purchase Index



Notes: This figure plots MBA U.S. Purchase Index, which represents weekly mortgage applications.

A. Identification Strategy

Due to endogeneity issues, establishing causality between housing article count and mortgage application is difficult. The causality (if present) can run either way. While my hypothesis is that more housing news prompts households to buy more houses, higher mortgage applications can also prompt the media to react by writing more about the housing market. To deal with this issue, I use FOMC meeting dates as IV. One of the main tools used by the Federal Reserve System (the Fed) for monetary policy is open market operations. Through open market operations, by buying and selling securities in the open market, the Fed maintains the federal funds rate[15] near the target rate.

The FOMC is a committee within the Fed responsible for the open market operations[16]. The

[15] "The interest rate at which deposit institutions lend reserve balances to other depository institutions overnight" (From the Fed website)

[16] While I focus on FOMC's setting of federal funds rate for this chapter, FOMC has different tools as well. These

Table 1. Data Sources

Data	Source	Notes
Housing News	NewsBank - “Access World News”	
Housing Price	Zillow	
Home Buying Interest	Google Trends	
National Articles	NewsBank - “Access World News”	Articles from “National” newspapers from “Access World News”
30 Yr Mortgage Rate	St Louis Federal Reserve	
New Constructions	U.S. Census - New Building Permits	I use total number of new units authorized
Mortgage Application	Mortgage Bankers Association - U.S. Purchase Index	
FOMC Meeting Dates & Forecasts	Bloomberg	

Notes: Table 1 summarizes the data used in this study.

FOMC holds eight regularly scheduled meetings per year, and the exact date of each meeting is confirmed in the previous meeting, which is at least a month in advance. One important objective of these meetings is the setting of a target for the federal funds rate, which is announced at the end of the meeting[17]. The federal funds rate plays an important role in the yield curve, and hence in mortgage rates and the housing market. As such, FOMC meetings are likely to lead to increased housing-related news. As the meeting dates are announced well in advance, the timing is exogenous. Furthermore, the market expectation of the FOMC's next target rate can be observable well in advance through economist forecasts.

For this study, I focus on FOMC meeting dates with zero standard deviation in the target rate forecasts and where the mean forecast target rate matched the actual decision. Namely, I focus on

include long-term yield targeting such as operation twist

[17]FOMC meetings can be a day or more than day. In this paper, when I refer to FOMC meeting day, I refer to the last day when the federal funds target rate is announced

FOMC meetings without any informational surprise. As the financial market is forward looking, an FOMC meeting that confirms what the market has no uncertainty about (as indicated by zero standard deviation in the target rate forecast) should not change anything fundamental about the housing market. This is consistent with Kuttner (2001), which finds that the interest rate reaction to the anticipated target rate is small. I argue that jump in housing news around no uncertainty FOMC meeting (if present) is plausibly exogenous. Linking this plausibly exogenous variation in number of housing related articles to subsequent increase in number of mortgage applications provides evidence that media causally affects households home-buying behavior. I consider 82 meetings between 1998 and 2015. The exact meeting dates and target rate decisions are listed in Table 2.

Analysis

In order to use FOMC meeting dates as an instrument for media housing count, I first test whether there is a jump in number of housing articles around FOMC meeting dates to check whether the first stage of 2SLS regression satisfies relevance condition. The regression specification is as follows.

$$N_t = F.E. + \underbrace{\sum_{j=1}^{3} \beta_j \mathbb{1}_{t+j}^{Meeting}}_{\text{Anticipation}} + \underbrace{\sum_{j=0}^{3} \beta_{j+4} \mathbb{1}_{t-j}^{Meeting}}_{\text{Reaction}} + \varepsilon_t \tag{2}$$

Here N_t is normalized national daily housing article counts. First, all housing articles are aggregated at daily level. In order to normalize the distribution of daily housing articles, I use $\log(n_t)$ where n_t is daily number of housing articles. Furthermore, weekly periodicity based on the day of the week is adjusted by regressing normalized housing news count on weekday dummies each year.

$\mathbb{1}_t^{Meeting}$ is a dummy variable, which is 1 if a FOMC meeting ended on a date t and 0 otherwise. I look at both whether number of housing articles increased in anticipation of FOMC meeting $\mathbb{1}_{t+j}^{Meeting}$ or in reaction to a meeting $\mathbb{1}_{t-j}^{Meeting}$. $F.E.$ is time fixed effects. I present results using year $\times$ month fixed effects but changing time fixed effects doesn't materially change results. The regression results are presented in Table 3

Table 2. No Surprise FOMC Meeting Dates

Date	Target Rate	Date	Target Rate	Date	Target Rate
12/22/1998	4.75	5/10/2006	5.00	11/2/2011	0.25
2/3/1999	4.75	9/20/2006	5.25	12/13/2011	0.25
3/30/1999	4.75	10/25/2006	5.25	1/25/2012	0.25
5/18/1999	4.75	12/12/2006	5.25	3/13/2012	0.25
6/30/1999	5.00	1/31/2007	5.25	4/25/2012	0.25
12/21/1999	5.50	3/21/2007	5.25	6/20/2012	0.25
3/21/2000	6.00	5/9/2007	5.25	8/1/2012	0.25
10/3/2000	6.50	6/28/2007	5.25	9/13/2012	0.25
11/15/2000	6.50	8/7/2007	5.25	12/12/2012	0.25
8/21/2001	3.50	6/25/2008	2.00	1/30/2013	0.25
3/19/2002	1.75	8/5/2008	2.00	3/20/2013	0.25
5/7/2002	1.75	8/12/2009	0.25	5/1/2013	0.25
6/26/2002	1.75	9/23/2009	0.25	6/19/2013	0.25
12/10/2002	1.25	11/4/2009	0.25	7/31/2013	0.25
8/12/2003	1.00	12/16/2009	0.25	9/18/2013	0.25
9/16/2003	1.00	1/27/2010	0.25	10/30/2013	0.25
10/28/2003	1.00	3/16/2010	0.25	12/18/2013	0.25
12/9/2003	1.00	4/28/2010	0.25	1/29/2014	0.25
1/28/2004	1.00	6/23/2010	0.25	3/19/2014	0.25
3/16/2004	1.00	8/10/2010	0.25	4/30/2014	0.25
5/4/2004	1.00	9/21/2010	0.25	6/18/2014	0.25
11/10/2004	2.00	11/3/2010	0.25	7/30/2014	0.25
2/2/2005	2.5	12/14/2010	0.25	10/29/2014	0.25
5/3/2005	3.00	1/26/2011	0.25	12/17/2014	0.25
8/9/2005	3.50	3/15/2011	0.25	1/28/2015	0.25
12/13/2005	4.25	4/27/2011	0.25	3/18/2015	0.25
3/28/2006	4.75	9/21/2011	0.25	4/29/2015	0.25
				10/28/2015	0.25

Notes: Table 2 lists all the no surprise FOMC meeting dates used in this study.

Due to the nationwide attention that the housing market received during the 2008 financial crisis, the dynamics of housing news count around FOMC meeting date is quite different pre-housing crisis (1998 to 2008) compared to post-housing crisis (2008-2015). Namely, while there appears to exist jump in housing news article count around FOMC meetings even when the outcomes of the meeting is essentially known, there appears to be no effect on housing news count prior the housing crisis. This difference in the results may reflect market's greater awareness in the housing market post housing crisis.

Looking at column (2), there doesn't seem to be any movement in housing news counts in

Table 3. Increase in Housing News Around FOMC Meeting Dates

		Normalized Daily Housing News	
		1998-2008	2008-2015
		(1)	(2)
Anticipation of Meeting	$\mathbb{1}_{t+3}^{Meeting}$	0.016	0.002
		(0.050)	(0.040)
	$\mathbb{1}_{t+2}^{Meeting}$	0.050	−0.009
		(0.048)	(0.051)
	$\mathbb{1}_{t+1}^{Meeting}$	0.016	0.057
		(0.063)	(0.070)
Reaction to Meeting	$\mathbb{1}_{t}^{Meeting}$	−0.074	0.099*
		(0.066)	(0.056)
	$\mathbb{1}_{t-1}^{Meeting}$	−0.063	0.038
		(0.049)	(0.050)
	$\mathbb{1}_{t-2}^{Meeting}$	−0.077	0.144**
		(0.054)	(0.063)
	$\mathbb{1}_{t-3}^{Meeting}$	−0.004	−0.033
		(0.056)	(0.042)
Fixed Effects		Year × Month	Year × Month
Observations		3,645	2,922
Adjusted R^2		0.047	0.094

Notes: Table 3 presents regression results estimating equation The parentheses contain year×month clustered standard errors. 2.* represents p<0.1, ** represents p<0.05, and *** represents p<0.01

anticipation of FOMC meeting. Rather, all of the movements in housing news count appears to in reaction to the meeting. On the day of meeting, there is 0.099 increase in normalized housing news count and there appears to be a stronger jump of 0.144 2 days after FOMC meetings. Between 2008-2015 my sample consists on average 3.33 normalized housing articles (27 articles daily), hence Table 3 suggests there were around 3-4% jump in housing related articles around FOMC meeting days between 2008-2015 even if the results of the meeting were essentially known.

As only post-housing crisis period satisfies relevance condition for 2SLS, subsequent analysis will only focus on 2008-2015. Intuitively, 2SLS analysis isolates exogenous variation predicted by an instrument (FOMC meeting date) and uses it to run correlation analysis on mortgage applications. One difficulty in this process is that the test for jump in housing news around FOMC meeting dates is conducted at daily scale where as mortgage applications data is only available at weekly scale. As can be seen in Table3, the jump in housing articles due to FOMC meeting is short-lived (decays in few days), and the scale of housing article count, aggregated at weekly level, is too big to capture any jump in housing articles due to FOMC meetings.

In order to resolve this issue, I test whether variation in Thursday and Friday housing article counts, predicted by whether there was a FOMC meeting during the week, has any predictive power on subsequent mortgage application. The U.S. Purchase index, described earlier, captures mortgage application activity between Saturday to Friday, and hence Friday and Thursday the week before, represent the most days that are not part of the mortgage application measurement period.

The regression specification for the 2SLS analysis is as follows.

$$X_t = F.E. + \delta Z_t + \nu_t \tag{3a}$$

$$Y_t = F.E. + \beta X_{t-1} + \varepsilon_t \tag{3b}$$

Here, $X_t = (N_t^{Friday}, N_t^{Thursday})'$, where $N_t^{Friday}, N_t^{Thursday}$ are normalized housing news count on Friday and Thursday of week t. $Z_t = (\mathbb{1}_t^{Tuesday}, \mathbb{1}_t^{Wednesday}, \mathbb{1}_t^{Thursday})'$, where $\mathbb{1}_t^{(\cdot)}$ is a dummy variable equal to 1 if there was a FOMC meeting on Tuesday, Wednesday, or Thursday and 0 otherwise. Y_t is normalized mortgage applications. I use percent difference in raw U.S. purchase index for Y_t. Time fixed effects, as before is year and month fixed effects. The regression result is summarized in Table 4.

Looking at Table 4, there is a statistical significant predictive power of FOMC meeting predicted jump in housing articles on subsequent mortgage applications. Looking at $N_{t-1}^{Thrusday}$, 1 unit increase predicted housing articles leads to 4% higher mortgage applications. Since the sample mean normalized housing articles is 3.33, this result suggests that when the number of housing articles doubles, subsequent mortgage application increases by 4%.

Table 4. Media on Mortgage Applications

	Normalized Weekly Mortgage Applications
N_{t-1}^{Friday}(fit)	0.051
	(0.197)
$N_{t-1}^{Thrusday}$(fit)	0.040**
	(0.019)
Observations	417

Notes: Table 4 presents regression results estimating equation 3. The parentheses contain year and month clustered standard errors. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01

V. Local Media on Local House Prices

As discussed in Section II, households get a heterogeneous news shock when there is a great deal of housing news due to costly information processing. With the presence of shorting constraints, only households with a positive news shock affect the housing market, creating a positive relationship between the number of housing news articles and housing returns. In the previous section, I provided an evidence, which suggests that households' home-buying decisions are affected by the media.

In this section, I provide evidence that suggests local housing news has short-term predictive power on local house prices, which is consistent with the model. I find that counties with higher numbers of housing news articles have housing returns 8-10 annualized basis points higher than other counties, and these appear 4-6 months afterward. This effect is persistent throughout the whole sample but is weakest during the housing crisis. Furthermore, the impulse response function from the panel VAR analysis suggests that this increase persists for 10 months after the increase in the housing content.

A. Does Housing News Content Predict Housing Returns?

I first use panel time-series regression to test whether housing-related content in the media predicts short-term local housing returns. I use the panel setup to identify the general relationship between the housing media and housing returns rather than the relationship at a certain regional setting. Panel time-series regression is useful because numerous economic factors may affect housing returns. Including county interacted with quarter fixed effects to control for local factors that vary at quarterly or less frequency.

The regression specification is as follows.

$$R_{it} = F.E. + \underbrace{\beta_1 \sum_{k=1}^{3} MI_{it-k}}_{\text{Quarter 1}} + \underbrace{\beta_2 \sum_{k=4}^{6} MI_{it-k}}_{\text{Quarter2}} + \underbrace{\beta_3 \sum_{k=7}^{9} MI_{it-k}}_{\text{Quarter 3}} + \underbrace{\beta_4 \sum_{k=10}^{12} MI_{it-k}}_{\text{Quarter 4}} + \sum_{k=1}^{36} \gamma_k R_{it-k} + X_{it} + \varepsilon_{it} \tag{4}$$

The main variable of interest is media increase MI_{it}, which measures the increase in housing news content in local newspapers between months t and $t-1$. For example, if housing-related newspaper articles increased between months t and $t-1$ for county i, MI_{it-k} would be 1, and 0 otherwise. I use the indicator for the increase in the number of housing articles rather than the amount of the increase because for small counties, housing articles are sparse and are essentially events[18].

Due to the significant processing time between a household's decision to buy or sell a house and the actual transaction, the unit of analysis is a quarter. Given that I am focused on the short-term predictive power of the media, I only include lags up to 1 year. According to the Home Buying Institute[19], on average, it takes at least 3-6 weeks for an individual to search for potential homes and another 1-3 weeks for mortgage underwriting and approval. Combined with the escrow and closing process, which takes 30-60 days, buying a home is at least a 2- to 3-month process. Due to this processing time, I expect most of the results to show up in β_2. Namely, I expect $\hat{\beta_2}$ to be positive and significant.

R_{it} is the one-month county-level housing return for county i at month t. This is computed as the log difference of the county's HPI. To account for the long-term auto-correlation exhibited by housing returns, 36-month lagged returns are included as controls. Although I present only results with 36 lagged returns, varying the number of lagged returns controls from 12 months to 48 months does not materially change the results. Lastly, to control for time-varying regional economic fundamentals, I include MSA interacted with year-quarter fixed effects to address MSA-

[18]I also use the changes in the numbers of housing articles for larger counties and obtain qualitatively similar results.

[19]The article can be found at http://www.homebuyinginstitute.com/how-long-to-buy.php

specific economic factors such as income, unemployment, housing permits, and interest rates that affect housing prices but do not change significantly month to month. Furthermore, MSA interacted with year-quarter fixed effects also addresses seasonality. As a robustness check, I also try including a number of fundamentals—national media, 30-year mortgage rate, and new construction—X_{it} as controls.

Table 5. Housing Article Increase on Subsequent Housing Return

	1 Month Local Housing return		
	(1)	(2)	(3)
Quarter 1	0.0004	0.001	0.0005
	(0.002)	(0.002)	(0.002)
Quarter 2	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
Quarter 3	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Quarter 4	−0.003	−0.003	−0.003
	(0.002)	(0.002)	(0.002)
Lagged Housing Returns	✓	✓	✓
Fixed Effects	MSA×Yr/Qtr	MSA×Yr/Qtr, Yr/Month	MSA×Yr/Qtr
Other Controls	No	No	Yes
Observations	46,226	46,226	46,226
Adjusted R^2	0.907	0.909	0.907

Notes: Table 5 reports the estimates for $\beta_1, \cdots, \beta_4$ in equation 4. Quarter 1 is number of months during last 3 months where number of housing articles increased. Quarter 2,3,4 are defined similarly. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01.

Table 5 summarizes the estimation results for equation 4. As indicated by equation 4, Quarter 1 is i, $i \in \{0, 1, 2, 3\}$ if there were i months in which number of housing articles increased during the last 3 months. Quarter 2 is i if there were i months in which the number of housing articles increased 4-6 months ago. Quarters 3 and 4 are defined similarly. Namely, Quarter $1, \cdots, 4$ provides estimates for $\hat{\beta}_1, \cdots, \hat{\beta}_4$. Each regression includes lagged 1-month housing returns up to 36 months and MSA interacted with year-quarter fixed effects. Column (2) includes year-month fixed effects to see if more frequently varying national fundamentals change the results. Column (3) includes controls—national media, 30-year mortgage rate, and new construction—as a robustness check.

In all three specifications, I find $\hat{\beta}_2$ to be positive and significant. Over the whole sample, counties with increases in housing news experience 0.6 bp (7.8 bp annualized) higher housing returns 4-6 months later. Including year-month fixed effects or other controls does not change the results, which suggests that MSA interacted with year-quarter fixed effects control effectively for time-varying fundamentals. For future tests, only MSA interacted with year-quarter fixed effects and 36-month lagged housing return are included. A 0.6 bp increase in monthly housing represents about 3% of the average monthly housing returns.

B. Crisis vs. Post Crisis

The period analyzed, 1998-2015, is made up of different periods that represent different points in the housing cycle. The US housing market experienced a housing boom in 2003-2007 and a housing crisis in 2008-2011. The recent era of 2012-2015 is a post-crisis recovery period. In this section, I test whether the local media effect persists throughout different phases of the housing market cycle. I use the same method as before but divide the sample into different parts.

Table 6 summarizes the regression results. Quarter $1, \cdots, 4$ is defined the same way as in Table 5. As with the whole-sample analysis (recapped in column (1)), the increase in local housing articles positively affects subsequent housing returns. As summarized in column (2), during the housing boom of 2003-2007, the Quarter 2 effect is 0.6 bp, which is identical to the whole sample, albeit with weaker statistical significance. There is a similar effect during the post-crisis period of 2012-2015. The Quarter 2 effect is slightly stronger at 0.8 bp.

During the housing crisis of 2008-2011, however, the local media effect disappears. One potential explanation is the proportions of positive and negative news. As can be seen in Figure 5, the proportion of positive news drops significantly during the housing crisis. As most of the housing news is negative during the crisis, the increase in housing articles does not substantially increase the proportion of households receiving a positive news shock. The differential effect of positive and negative news is considered as an extension and is discussed in Appendix B.

Another interesting observation is that there is strong reversion during Quarter 4 for the housing

Table 6. Housing Article Increase on Subsequent Housing Return: Sub-Samples

	1 Month Local Housing Return			
	Entire Sample	Housing Boom (2003-2007)	Housing Crisis (2008-2011)	Post-Crisis (2012-2015)
	(1)	(2)	(3)	(4)
Quarter 1	0.0004	0.001	0.005	−0.002
	(0.002)	(0.004)	(0.005)	(0.005)
Quarter 2	0.006***	0.006*	0.003	0.008*
	(0.002)	(0.004)	(0.005)	(0.005)
Quarter 3	0.002	−0.001	0.001	0.007
	(0.002)	(0.004)	(0.005)	(0.005)
Quarter 4	−0.003	−0.010***	−0.005	0.013***
	(0.002)	(0.004)	(0.005)	(0.005)
Lagged Housing Returns	✓	✓	✓	✓
Fixed Effects	MSA ×Yr/Qtr	MSA×Yr/Qtr	MSA×Yr/Qtr	MSA×Yr/Qtr
Observations	46,226	13,920	11,136	11,136
Adjusted R^2	0.907	0.925	0.885	0.856

Notes: Table 6 reports the estimates for β_k in equation 4 in different time periods. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01.

boom period. One potential explanation for this is the change in the housing supply. The change in new construction following the increase in housing news is explored in the Appendix A. Overall, the regression results show that the media effect is stable throughout the housing market cycle.

C. Impact of Housing Media Increase over Time

In the previous section, I showed that an increase in housing-related articles is correlated with increased housing returns 4-6 months afterward. In this section, to address issues with potential reverse causality and to analyze the lasting impact of housing news, I use panel vector auto-regression (VAR) analysis and the impulse response function.

The regression specification is as follows:

$$Y_{it} = \sum_{k=1}^{K} A^k Y_{it-k} + BX_{it} + e_{it} \tag{5}$$

Here, $Y_{it} = (R_{it}, MC_{it})'$, where R_{it} is the 1-month housing return for county i during month t. Media change, MC_{it}, is 1 if the housing content increased in county i during month t, -1 if the housing content decreased, and 0 if it did not change. A^k is the 2×2 matrix of coefficients. e_{it} is the 2×1 vector or error terms.

Lastly, $X_{it} = (\overline{R}_{it}, \overline{MC}_{it})'$ are proxies for local economic fundamentals. Similar to the panel time-series regression fixed effects, these are measured as the average housing return and average housing content increase of county months in a given MSA-quarter. For example, to obtain $\overline{R}_{it}$ in January 2009, I average all of the housing returns between January 2009 to March 2009 from all of the counties in the same MSA as county i.

Hence, equation (3) is identical to the system of equations

$$R_{it} = \sum_{k=1}^{K} A_{11}^k R_{it-k} + \sum_{k=1}^{K} A_{12}^k MC_{it-k} + B_{11}\overline{R}_{it} + B_{12}\overline{MC}_{it} + \varepsilon_{it} \tag{6a}$$

$$MC_{it} = \sum_{k=1}^{K} A_{21}^k R_{it-k} + \sum_{k=1}^{K} A_{22}^k MC_{it-k} + B_{21}\overline{R}_{it} + B_{22}\overline{MC}_{it} + \varepsilon_{it} \tag{6b}$$

Here, A_{ij}^k and B_{ij} is the ith row jth column element of matrices A^k and B.

I follow Abrigo, Love, et al. (2015) in the assumptions and panel VAR estimation. One necessary assumption is for the error terms to be non-correlated over time—that is, $\mathbb{E}[e_{it}' e_{is}] = 0, \forall t > s$. With the inclusion of sufficient controls for lagged returns, I assume this to be true. I report the regression result for $K = 12$ and, given other studies' use of 12 months to correct for autocorrelation (Soo, 2013), I argue that assuming zero serial correlation of error terms with 12-month lag controls is reasonable[20].

The estimation result for equation 5 is presented in Table 7. The first two columns report the coefficient estimates with R_{it} as the dependent variable, and the last two columns report the coefficient estimates with MI_{it} as the dependent variable. The coefficient estimates for B are not

[20] K between 12 and 36 does not materially change the result

Table 7. Panel VAR on Housing Return and Media Housing Content

	R_{it}		MC_{it}	
k	R_{it-k}	MC_{it-k}	R_{it-k}	MC_{it-k}
1	1.085***	-0.001	-0.004	-0.523***
	(0.017)	(0.001)	(0.014)	(0.004)
2	-0.838***	0.001	-0.003	-0.245***
	(0.028)	(0.002)	(0.02)	(0.005)
3	0.406***	0.003*	0.034	-0.071***
	(0.039)	(0.002)	(0.023)	(0.005)
4	0.047**	0.003*	-0.061**	-0.034***
	(0.041)	(0.002)	(0.024)	(0.005)
5	-0.308***	0.001	0.078***	-0.021***
	(0.038)	(0.002)	(0.024)	(0.005)
6	0.367***	0.003*	-0.073***	-0.01*
	(0.031)	(0.002)	(0.024)	(0.005)
7	-0.243***	0.002	0.037	-0.004
	(0.023)	(0.002)	(0.024)	(0.005)
8	0.094***	0.001	0.003	-0.013**
	(0.02)	(0.002)	(0.024)	(0.005)
9	0.031	0.001	-0.021	-0.001
	(0.02)	(0.002)	(0.024)	(0.005)
10	-0.048***	-0.001	0.018	-0.009*
	(0.019)	(0.002)	(0.023)	(0.005)
11	-0.003	0.001	-0.002	-0.012**
	(0.015)	(0.002)	(0.019)	(0.005)
12	-0.012	-0.001	0.007	0.01**
	(0.008)	(0.001)	(0.011)	(0.005)

Notes: Table 7 reports the estimates for equation 5. The first two columns represents estimates with R_{it} as the depedent variable. The last two columns represents estimates with MI_{it} as the dependent variable. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01.

presented. As expected, due to the well-documented auto-correlation of housing returns, the first column contains many significant estimates. Toward the end of 12 months, the significance wanes, giving more credibility to the assumption of zero auto-correlation among the error terms. More relevant are the coefficients in the second column. There are positive and significant relationships between the increase in housing-related articles and housing returns 3, 4, and 6 months afterward.

Housing returns also appear to have some reverse effect on housing articles. There also seems to be strong mean reversion in the MC_{it}, which is expected. Housing news for many counties comes out infrequently, and a decrease in housing news necessarily follows an increase.

Figure 7. Impulse Response Function

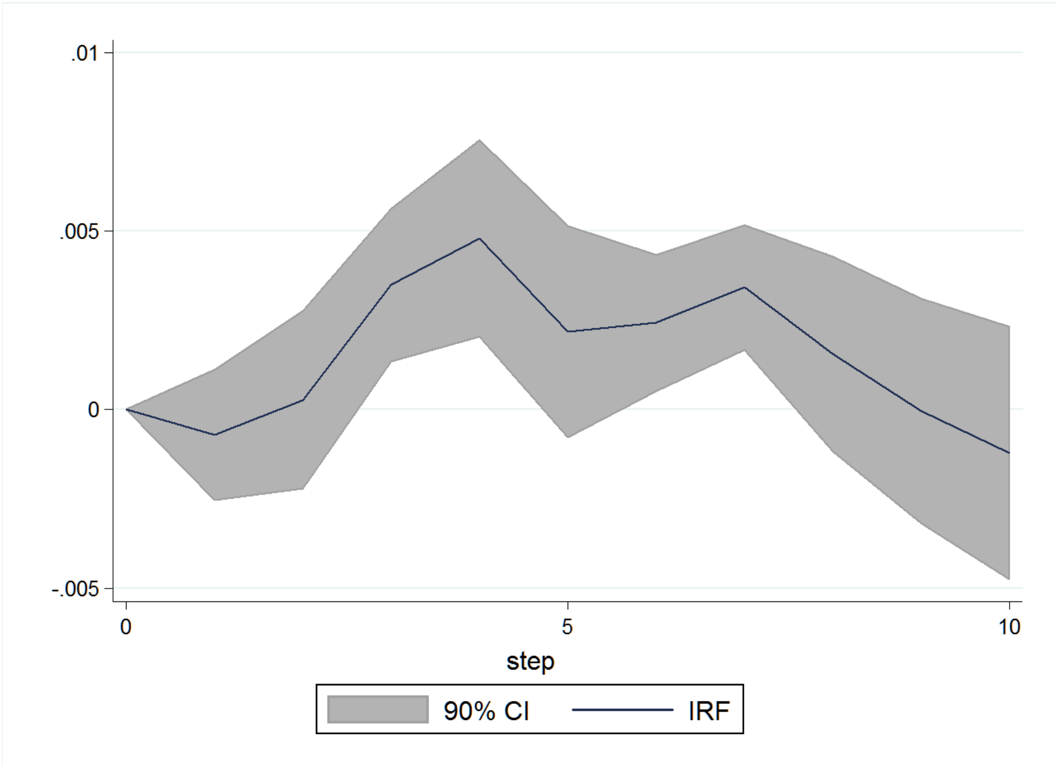


Figure 7 plots the impulse response function of increased media housing content on housing returns. The grey band represents the 90% confidence interval based on 10 simulations. Due to the contemporaneous effect of past housing returns on housing news, the media effect estimated is smaller, around 0.5 bp. However, an increase in the media's housing content still appears to lead to an increase in housing returns that peaks at month 4. The effect, however, mostly dissipates after month 9.

The dissipation of the media effect after month 9 can be partially explained by the change in supply. In the model described in Section II, I assume that the housing supply is provided only by households selling homes because new construction takes 6 months on average. If new homes are constructed due to increased housing demand, the local media effect can dissipate. Assuming that the construction of new homes begins at the peak of the local housing effect (3-4 months after the news), new homes would start entering the market about 9 months after the news. I provide rough evidence of this in Appendix A.

VI. Conclusion

The residential housing market is dominated by households, and households have been documented to exhibit behavioral anomalies and high sensitivity to the media. Hence, it is likely that the media affect households' home-buying behavior, which in turn translates into short-term home price dynamics. I document few pieces of evidence, including a plausibly causal one, that support this hypothesis.

I first provide an evidence that the media affect households' home-buying decisions through the use of no-surprise FOMC meetings as an IV. I argue that jumps in housing articles around no-surprise FOMC meeting days are plausibly exogenous, and these jumps' predictive power on subsequent mortgage applications is a plausibly causal evidence.

I also document a strong correlation between changes in lagged media coverage of the housing market and subsequent changes in local housing returns. Counties with positive housing news experience returns 8-10 annualized basis points higher than other counties. I suggest that this is due to the shorting constraint in the housing market. Households can respond only to positive housing news, and as positive news is more likely when the absolute number of housing news articles increases, housing news change is positively correlated with subsequent housing return change.

Much work remains to be done in regard to this topic. Perhaps the most important work is to develop a setting that allows more robust testing of the causal story between the media and housing market. Further quantification of the lasting impact of the media on the economy and asset prices through their effects on households' home-buying behavior is also needed.

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Appendix A. Local Housing Media and New Construction

In this section, I provide evidence that new construction may cause the local media effect to dissipate after about 9 months. I show this by documenting the increased number of building permit approvals 3-5 months after an increase in local housing news. As the construction of new units takes about 6 months on average, an increase in the housing supply 9-11 months later may explain why the local housing news effect dissipates after 9-11 months.

Building permits take 2 months to be approved on average. Hence, the correlation between the lagged increase in local housing news and building permit approval may be due to construction companies responding either to increased household home searches or to the local news shock. For example, construction companies receiving heterogenous signals from local media that are only able to respond to a positive housing shock provide an analogous result to the model described in Section II.

The regression specification is similar to that used before, with several changes. The specification is as follows.

$$NP_{it} = F.E. + \sum_{k=1}^{12} \beta_k MI_{it-k} + \sum_{k=1}^{12} \gamma_k^1 R_{it-k} + \sum_{k=1}^{12} \gamma_k^2 NP_{it-k} + \varepsilon_{it} \tag{A1}$$

The dependent variable is the change in New Permits (NP) for county i at month t. The source of new permit data is shown in Table 1. The numbers of permit grants differ across different counties, so I divide by the whole sample average to standardize the data. As many of the data points are imputed, data for counties with few new permits are likely to be noisier than data for counties with more construction. As such, I use only data from counties with at least 100 monthly average permit grants in the sample. Matching the newspaper and building permit data yields 106 counties. As before, MI_{it} is the increase in housing-related media for county i at month t. I include up to 12-month lags of the local housing return R_{it} and new permits as controls.

Table 8 summarizes the regression results. Due to space constraints, I report only β_k for up to 6 months, but β_ks for 7- to 12-month lags are statistically indifferent from 0. Column (1) summarizes the result for the whole sample (2000-2015), and columns (2), (3), and (4) summarize the results for the subsamples. Looking first at the whole sample, media increase appears to have strong

Table 8. Lagged Local Housing Media on Building Permit Changes

	Change in New Building Permit			
	All	2004-2007	2008-2011	2012-2015
	(1)	(2)	(3)	(4)
Lagged 1 Month	−0.003	−0.012	0.002	−0.005
	(0.009)	(0.017)	(0.014)	(0.021)
Lagged 2 Month	−0.004	0.005	−0.006	−0.010
	(0.011)	(0.020)	(0.016)	(0.025)
Lagged 3 Month	0.024**	0.040*	0.011	0.019
	(0.011)	(0.021)	(0.017)	(0.026)
Lagged 4 Month	0.027**	0.024	0.032*	0.032
	(0.011)	(0.021)	(0.017)	(0.027)
Lagged 5 Month	0.018*	0.032	0.006	0.013
	(0.011)	(0.021)	(0.017)	(0.027)
Lagged 6 Month	0.013	0.039*	0.008	−0.007
	(0.011)	(0.021)	(0.017)	(0.027)
Lagged Returns	✓	✓	✓	✓
Lagged New Permits	✓	✓	✓	✓
Fixed Effects	County, Yr/Mon, MSA × Yr/Qtr	County, Yr/Mon, MSA × Yr/Qtr	County, Yr/Mon, MSA × Yr/Qtr	County, Yr/Mon, MSA × Yr/Qtr
Observations	18,974	18,974	18,974	
Adjusted R^2	0.418	0.417	0.429	

Notes: Table 8 predictive power of media increase on subsequent new permit approvals. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01.

predictive power for subsequent changes in the number of new building permits. Increases in new building permits are 1.8-2.4% higher for counties that had increases in housing news articles 3-5 months prior.

Considering the subsamples, the predictive power of the media on new building permits appears to be strongest in the 2004-2007 sample. The change in the number of new building permits appears to be 4% higher for counties that had increased housing news 3 months prior. In the 2008-2011 sample, the change in the number of new building permits is 3.2% higher for counties with increased housing news 4 months prior. The significance disappears in the 2012-2015 sample. The predictive relationship is strongest in 2004-2007 and weaker in subsequent periods, which is consistent with the media effect reversion reaching its strongest state during the 2003-2007 period in Table 6.

Appendix B. Decomposing Housing Media

In this section, I explore an extension in which I decompose the housing media into positive and negative news via text analysis. Although this is an informative exercise, because of the noisiness of the decomposition due to my access to only the headlines, this exercise is included only in the appendix.

Classifying Articles

The biggest challenge in this analysis is classifying the articles into positive and negative categories. As mentioned previously, because of my institution's contract with NewsBank, I do not have access to the body of sample articles[21]. Instead, I rely on the headlines to determine the content of each article.

To objectively classify headlines as positive or negative, I follow the text-mining approach used by Tetlock (2007). I start with the Harvard IV-4 (HIV4) Dictionary of positive and negative words. As highlighted by numerous studies using this approach (Engelberg, 2008; Tetlock, Saar-Tsechansky, and Macskassy, 2008), using the HIV4 dictionary without any supplement can lead to inaccurate and noisy classifications. To increase the accuracy of my headline classification, I follow an approach suggested by Loughran and McDonald (2011)[22] and manually add the most used words that are likely to be used in positive and negative housing market contexts. Ultimately, a headline is classified as positive or negative depending on whether it contains more positive or negative words. Table 9 includes my addendum to the HIV-4 dictionary.

I limit the sample of articles to those with "home," "house," or "housing" in the headlines to filter out headlines such as "Online sales grow by 19% - Amazon.com leads retailers"[23], which has a positive sentiment but does not provide information about the housing market.

Table 10 lists a random sample of 25 selected headlines and their classifications. Of the 25

[21] Downloading article bodies for over 200,000 articles would require webscraping, which the contract prohibits

[22] Loughran and McDonald (2011) does not actually use this approach because it may lead to endogeneity problems. In the context of corporate finance, managers may decide to consider these results in future annual reports. However, this problem is not a concern with media and household behaviors.

[23] "Online sales grow by 19% - Amazon.com leads retailers" talks about the sluggish housing market as a factor of consumer spending. Hence, if sentiment analysis on the article body were to be run, it would be classified as a negative housing article. For this analysis, the article is excluded.

Table 9. Words added to Harvard IV-4 Dictionary

Positive Words	Negative Words
up, climb, soaring,	down, worst, slowly,
rise, highest, highs,	fall, bottom, lose,
increase, increases, advance,	drop, lowest, dropped,
rising, positive, surges,	decline, downturn, slower,
higher, grow, recovering,	slow, tumble, lows,
jump, improve, increasing,	lower, bust, dips,
rebound, boosts, gains,	slump, concerns, loses,
strong, grows, upagain,	falls, slowdown, slips,
better, spike, hope,	bad, slows, dropping,
surge, hike, stabilize,	dip, declines, cloudy,
gain, increased, top-mover,	weak, distressed, ominous,
rises, upward, growing,	less, meltdown, gloom,
rose, recover, life,	falling, slowing, repossessions,
rally, improves	worries, worse, difficult,
	plunge, struggling, decrease,
	fell, sluggish

Note: This table lists words that are added to Harvard IV-4 dictionary to classify sentences into positive and negative sentences. These are words that appear most frequently in the headline dataset that are manually determined likely to have positive or negative meaning when used in housing market context.

headlines, 16 include the terms "home," "house," or "housing" and are hence included in my sample. Although not perfect, the classification method appears to perform adequately. Aside from one error ("House sales decrease; unemployment rate rises") and several ambiguous cases (e.g., "Real estate sales slide in Myrtle Beach area - Home prices rise; condos continue to fall,"), classifications based on this method appear to be more or less accurate.

Positive and Negative Articles on Housing Returns

As with previous analyses, I use the panel time-series regression with controls for lagged returns and region-time fixed effects. Table 11 summarizes the regression results. As with Table 6, I divide the analysis into the whole sample and three different subsamples. The first panel reports the estimates for increases in positive housing articles. The second panel reports the estimates for increases in negative housing articles.

As seen in the column (1), an increase in positive news leads to an increase in housing returns. Although there seem to be similar effects for negative news, the coefficients are not statistically

Table 10. Sample Headlines

Headline	Positive Words	Negative Words
Clean Clicks vs. Dirty Data What would it take to build an environmentally sustainable internet? - Insurers and financial corporations are pushing for new laws and policies to fight climate change before it hits their bottom lines. It might not be altruism, but it just might work.	0	1
US homebuilders' confidence in sales surges in June	1	0
Existing home sales teeter in September - 1.9% drop blamed on higher prices and interest rates	1	1
Reel logic: Choosing a fishing reel boils down to skill level and application choices	0	1
US home prices up 9.3 pct., most in nearly 7 years	1	0
Oil falls as growth worries outweigh positive news	1	2
Rise in US home sales reflects steady improvement	1	0
Rise in home building suggests industry turnaround	1	0
Survey: Home prices increase in half of major U.S. cities	1	0
Mass. housing prices firm, sales fall	0	1
Real estate sales slide in Myrtle Beach area - Home prices rise; condos continue fall	1	1
BROWARD HOME SALES, PRICES DOWN IN THIRD QUARTER	0	1
Banks put up roadblocks to low mortgages	1	0
CHOPPY MARKET MOVES HIGHER AS DOW RISES 75	2	0
Real estate recovering, albeit slowly - In Darien	1	1
One step ahead - Real estate agent helps struggling homeowners in poor economyFACES OF IDAHO	0	1
Existing-home sales rise, fueling hopes of recovery Rebound in national market seen as critical step in exiting recession	2	0
New-home sales up 11% - Low prices, tax credits boost increase	2	0
Median home prices fall in 88 percent of cities	0	1
Stocks tumble as oil falls on economic worries	0	3
Analysts adjust oil-cost forecast - Global financial crisis is forcing them to lower their initially high price predictions	0	1
Coldwell Banker to drop home prices for 10 days in Valley - 173 houses will be discounted 5-12% in the latest promotion by a real estate company or builder.	0	1
House sales decrease; unemployment rate rises	1	1
Weak sales, write-downs send homebuilder Lennar to 1Q loss	0	1
Dixie sales tumble; profit slips	0	2

Note: This table lists 25 randomly picked headlines that has at least one positive or negative word. Postive and negative words attached to the Harvard IV-4 dictionary are listed in Table 9

significant. In contrast to previous analysis, positive news seems to be strongest during the first quarter rather than the second quarter. Given the heterogeneity in home-buying process times,

Table 11. Increase in Housing Article (Positive / Negative) on Subsequent Housing Return

		1 Month Local Housing Return:			
		All	2003-2007	2008-2011	2012-2015
		(1)	(2)	(3)	(4)
Positive Article Increase	Quarter 1	0.006**	−0.0004	0.015**	0.006
		(0.003)	(0.005)	(0.006)	(0.006)
	Quarter 2	0.003	−0.007	0.004	0.013**
		(0.003)	(0.005)	(0.006)	(0.006)
	Quarter 3	−0.002	−0.005	−0.007	0.003
		(0.003)	(0.005)	(0.006)	(0.006)
	Quarter 4	0.001	0.001	−0.011*	0.013**
		(0.003)	(0.005)	(0.006)	(0.006)
Negative Article Increase	Quarter 1	−0.003	−0.008	−0.006	0.002
		(0.003)	(0.005)	(0.006)	(0.007)
	Quarter 2	−0.002	−0.001	−0.006	0.005
		(0.003)	(0.005)	(0.006)	(0.007)
	Quarter 3	0.002	0.016***	−0.002	−0.008
		(0.003)	(0.005)	(0.006)	(0.006)
	Quarter 4	−0.001	−0.001	−0.006	0.005
		(0.003)	(0.006)	(0.006)	(0.006)
	Lagged Housing Returns	✓	✓	✓	✓
	Fixed Effects	MSA ×Yr/Qtr	MSA ×Yr/Qtr	MSA ×Yr/Qtr	MSA ×Yr/Qtr
	Observations	46,226	13,920	11,136	11,136
	Adjusted R^2	0.907	0.925	0.885	0.856

Notes: Table 11 reports effect of increase in positive and negative articles on subsequent local housing return in different periods. * represents p<0.1, ** represents p<0.05, and *** represents p<0.01.

this result is not surprising. Considering the subsamples, there appears to be a strong effect from positive housing news during the housing crisis (column (3)) and post-crisis (column (4)). However, during these periods, negative housing news has no effect.

During the housing boom period (column 2), I find no effect for positive housing news. Instead, negative housing news has a strong effect during Quarter 3. The coefficient suggests that an increase in negative housing news during the housing boom is correlated with a 1.6 bp higher housing return 7-10 months afterward. Although negative news leading to higher returns may seem counterintuitive, it may indicate a reversal of the decline in housing returns accumulated during months 1-6.

While lacking statistical significance, these results are consistent with the implications of the model described in II. Namely, positive news is likely to induce households to buy homes, positively affecting the local hpi, while negative news is less likely to affect the local hpi due to shorting constraints. At the very least, this result suggests that future work dissecting into the contents of local news articles may be beneficial.