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Desperate House Sellers: Distress Among Developers

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Desperate House Sellers: Distress Among Developers

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Abstract

Using granular data on home builder housing developments from the 2006-09 housing crisis, I show that builders spread house price shocks across geographically distinct projects via their internal capital markets. Builders who experience losses in one area subsequently sell homes in unaffected areas at a discount to raise cash quickly. Financially constrained firms are more likely to cut prices of homes in healthy areas in response to losses in unhealthy ones. Firms also smooth shocks across projects only during the crisis and not during the boom. These results together suggest firm internal capital markets spread negative economic shocks across space.

1 Introduction

Financial frictions can negatively affect economic activity. These frictions prevent firms from accessing external funds, forcing them to rely on internal cash flows (Myers and Majluf, 1984). From 2003-2009, internal funds made up 85% of total corporate financing.¹ When firms rely on internal financing, shocks to one part of the firm can propagate to other parts.² These within-firm spillovers are important because they cause firms to reduce investment in positive NPV projects when financing constraints bind.³ These spillovers also indicate that economic activity in different industries is linked through firms' internal networks. But evidence of within-firm spillovers affecting prices is limited.⁴ I present new findings on within-firm price spillovers using granular data on the geographically distinct housing developments of home builders. I show that during the 2006-09 housing crisis, when builders lost money on one project, they cut prices on homes they had for sale in healthy, geographically distant projects in order to speed up sales and generate cash quickly.

The home building industry provides a natural laboratory to study internal capital markets, overcoming several of the empirical concerns that make investigating this subject difficult. One of these concerns is the inability to precisely measure projects and their NPVs within a firm. Conglomerate segment data, which has been used extensively in the past, is often imprecise and has been found inaccurate (Whited, 2001). A second concern is endogeneity. Investment across different projects within a firm may be correlated because firms subsidize failing projects with funds from healthy ones, or because all projects are exposed to the same economic shocks. For example, different firm projects will experience the same

¹See the Board of Governors of the Federal Reserve System, Flow of Funds Accounts of the United States, Table F.103.

²There is a large literature on internal capital markets, including work by Gertner et al. (1994), Rajan et al. (2000), Scharfstein and Stein (2000), and Stein (1997). Early seminal works in this area include Alchian (1969) and Williamson (1975).

³See Lamont (1997), Peek and Rosengren (2000), Giroud and Mueller (2017), Mondragon (2018) and Cetorelli and Goldberg (2012).

⁴See e.g. Ge (2017), described in Section 1.1.

shock if the projects are located in the same area and therefore share exposure to the same local economic conditions (Chevalier, 2004). My approach addresses both these concerns because I use granular data on housing developments to identify firm projects. These projects are geographically distinct and therefore vary in their exposure to the 2006-09 housing crisis.

I find that a 10% (\sim one standard deviation) decrease in the value of a builder's projects in other markets leads to a 2.2% decrease in her house prices in unaffected areas. Models of internal capital markets suggest that firms tend to cross-subsidize projects when access to external financing is costly. Consistent with these models, I find that financially constrained builders are more likely to spread shocks across projects. I also find no effect during the 2002-05 housing boom, a period when financing constraints did not bind because builders could easily obtain credit. I show that when builders cut prices they sell homes more quickly and that builders spread price shocks more to areas where a price cut produces a larger decline in time-to-sale.

To analyze this industry, I construct a unique dataset of builder home sales matched to builder finances. I start with a Corelogic dataset of housing transactions, which records rich information on the characteristics of homes, such as square footage and property type. I use these variables to control for differences in home quality between builders that would otherwise confound the results. Next, note that if builders cut prices in healthy areas due to internal capital markets, then the tendency to cut prices should correlate with builder financial constraints. To test this hypothesis, I construct a variety of measures of financial constraints, some that are generic in the corporate finance literature and some that are unique to the home building industry and merge these to builder home sales. Finally, to investigate if constrained builders cut prices to speed up sales, I gather data from realtor listings that report homes' time on the market and merge these listings to home sales. The resulting dataset reports a home's location, price, quality, and time-to-sale, creating a novel setting to study internal capital markets and prices.

To conduct my empirical analysis, I compare prices for observationally identical homes

sold in the same zip code and year by different builders who differ in their exposure to house price shocks in other areas. I measure a builder’s exposure to price shocks as the weighted average change in prices in counties where the builder operates, with weights that reflect the importance of each county in the builder’s overall portfolio. If I were to evaluate the effect of a builder losing money in a given county on the builder’s pricing in that same county, then any effect I find would be contaminated by local economic conditions. In contrast, in my empirical design I separate local economic conditions from the builder’s condition by evaluating a constrained builder’s pricing in a region separate from the one in which the builder initially lost money. The effect is likely an underestimate because when shocked builders cut prices, the prices of non-shocked builder homes may fall due to comparable pricing.⁵ To test this, I show that when builders sell homes at a discount, the prices of nearby, non-builder resale homes decline. In addition, the effect increases when I compare the pricing of shocked and non-shocked builders within small time frames where comparable pricing matters less.

The validity of my analysis rests on the assumption that a builder’s initial decision to build in a housing bust area is independent of his potential pricing.⁶ This assumption will be violated if the house price shock affects all regions and the builders who located in bust areas serve a clientele more negatively affected by the common shock. To address this problem, I perform a number of tests. First, if builders with exposure to bust markets, (shocked), cater to a different clientele than builders without that exposure, (non-shocked), then I would expect these builders to also differ in pricing before the 2006-09 crisis. To test this, I show graphically that pricing for shocked and non-shocked builders only diverges during the crisis period and not before. Second, if shocked builders sold to a different socio-economic group, then there should be a difference in the luxury, quality, and neighborhood of the homes these

⁵See Campbell et al. (2011) and Guren (2018).

⁶The housing bust period refers to years 2006-09 and the housing boom period refers to years 2002-05 throughout.

builders sell. To address this possibility, I show the effect remains robust to controlling for zip code by year fixed effects and a host of variables describing home quality.

1.1 Related Literature

My results contribute to a broad literature in corporate finance on internal capital markets. Papers in this area show that internal capital markets affect investment (Lamont, 1997),⁷ employment (Giroud and Mueller, 2017), and lending (Peek and Rosengren, 2000). Ge (2017) also studies how internal capital markets affect prices but focuses specifically on the life insurance industry, showing that distressed insurers lower premiums on contracts that increase firm capital. Little is known about the effect of internal capital markets on prices in durable goods industries, where buyers and sellers face search frictions and sellers must invest time to find a buyer with a high value for their good. I show in the home builder industry that firms respond to a loss in one project by slashing prices in geographically distant projects, and I use detailed time-to-sale data from listings records to show that firms cut prices to speed up sales. My findings have implications for price contagion in other durable goods industries, such as the automobile and household goods industries.

In addition, my findings contribute to a growing literature on the propagation of local geographic shocks (Bailey et al., 2017; Benmelech et al., 2014; Campbell et al., 2011; DeFusco et al., 2018; Notowidigdo, 2011). Giroud and Mueller (2017) show that when a negative economic shock affects one branch of a firm, the firm cuts employment in other, geographically distant branches. I also show that firms spread negative economic shocks across geography via their internal networks, but my paper has several important differences from theirs. First, whereas Giroud and Mueller (2017) study employment, I study pricing, a new margin of geographic contagion. Second, Giroud and Mueller (2017) do not observe data on firm clientele, leaving them less able to address the concern that a firm cuts employ-

⁷See also Berger and Ofek (1995), Lang and Stulz (1994), and Shin and Park (1999).

ment in an unaffected project because the firm’s clientele has reduced demand. In contrast, I have granular data on the physical characteristics of homes that builders sell which I use to capture clientele differences between builders which would otherwise confound the results.

I also contribute to the literature on financial distress and prices. (Benmelech and Bergman, 2008, 2009, 2011; Ortiz-Molina and Phillips, 2010; Pulvino, 1998). Theory suggests that distressed firms, unable to access external finance, sell equipment at a discount to industry outsiders in order to raise cash quickly (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Shleifer and Vishny, 1992, 2011). I add to this literature by connecting fire sales to internal capital markets. I show that builders do not restrict fire sale behavior to a single floundering project, but also sell off assets from healthy, unrelated projects when in distress. This paper is also related to the literature on the effects of financial distress on inventory prices. Other work has studied this relationship for supermarkets, (Chevalier, 1995), consumer goods, (Kim, 2018), and goods underlying the PPI (Gilchrist et al., 2017). Using granular data on product quality, price, and time-to-sale, I show in a durable goods industry that distressed firms discount prices on inventory in order to make sales quickly.

Lastly, my findings add to a literature on home builders in a housing downturn. Haughwout et al. (2012) and Nathanson and Zwick (2017) show that during the last housing boom, home builders over-developed and created an excess supply of homes, fueling the subsequent bust in house prices. My results provide evidence that home builders further contribute to housing downturns by cutting home prices in unaffected regions.

2 Home Building Overview

2.1 Home Building Business Landscape

The home building industry is an important part of the U.S. economy. In 2017, 13% of homes sales were of newly constructed homes, with a total market size of roughly \$236

billion. During the last housing boom the industry was even larger; in 2005, at a market size of approximately \$381 billion, it was responsible for 20% of home sales.⁸ However, despite its considerable size, the industry is also fragmented, with a few large firms and many small builders. In 2007, the U.S. Economic Census reported a total of 98,067 home builders. These builders range from large, publicly traded firms producing thousands of homes a year, to one-person contractors hired by a home buyer to build a home to their specification. Indeed, in 2007, 65% of home builders had sales receipts of less than \$1 million. In this paper, I focus on the large home building firms for two main reasons. First and foremost, small contractors are unlikely to have more than one home on the market at any one time, and therefore would not exhibit any kind of cross subsidizing behavior across distinct developments. Furthermore, small builders are not geographically dispersed enough for their separate housing projects to experience different shocks.⁹

Builders' housing developments are constructed separately from each other and take three to five years to develop. Builders buy land, develop the parcels, hire subcontractors to construct homes on the parcels, and then sell those homes directly to households via their in-house real estate agents. Builders construct both made-to-order and ready-made homes, called "speculative" homes. Once a contract for a made-to-order home with a home buyer is struck, the builder hires subcontractors to build the home to the preferences of the buyer. Consequently, builder inventory consists mostly of tracts of land and partially and fully completed homes. Builders often purchase land parcels using options, giving them the right to buy the land outright at a certain price within a given time. Option prices tend to be around 10% of the actual land value. When land values plummeted during the crisis, builders with more of their land owned via options rather than owned outright should have enjoyed a stronger financial position.

⁸See the U.S. Census, New Residential Sales, the Department of Housing and Urban Development, and the National Association of Realtors.

⁹The large builders make up approximately 25% of new home sales in 2009.

The large home builders have wide geographic dispersion. To illustrate this, Figure 1 reports the concentration in 2009 across U.S. counties of homes sold by the builders in my sample in 2009. Builders operated in the West, Southwest, and along the eastern seaboard, areas which experienced very different house price trajectories during the last crisis. My sample, which is described in detail in Section 4, contains roughly 2,000 large builders. Table I reports summary statistics on the geographic dispersion of these builders. In this sample, the average builder sells 72 homes per year and operates in approximately 3 different states. The number of states a builder builds homes in is not a complete measure of geographic spread, since a builder may technically operate in two states but sell 99% of his homes in one state, and 1% in the second. To get a better sense of a builder's concentration across states, I construct a geographic HHI equal to the squared sum of the fraction of homes a builder sells in each state. The average builder in my sample has an HHI of 0.51, suggesting equal concentration across two states. Public home builders are larger and more dispersed than private ones; the average public home builder sells 4,265 homes per year and operates in 14 states.

2.2 Home Building Financing

This paper focuses on large builders, defined as selling more than two homes per year and operating in more than one county. The analysis of builder finances focuses on the subset of large builders which are publicly traded and therefore report financial information. Public builders finance themselves using cash from operations, unsecured public debt, revolving credit facilities, mortgage notes, and operating leases. In Table I, I report summary statistics on builder financing taken from the annual reports of public builders. Large public builders have an average leverage ratio of 0.39, defined as the ratio of total debt to total assets.

From the 1970s, when the large home builder industry arose, until 2007, land prices had

Table I
Builder Summary Statistics

This table reports summary statistics of builders in the sample in 2009 with public firms reported separately. Geo. HHI is equal to the squared sum of the fraction of homes a builder sells in each state. The financial statistics of public home builders are calculated in 2006. *Leverage*₀₆ is defined as the ratio of total debt to assets. *Coverage*₀₆ is defined as the ratio of *EBIT* to interest expense. *Pct.Eq.Subs*₀₆ is defined as equity in subsidiaries as a percent of assets. *CashtoAssets*₀₆ is defined as the ratio of cash to assets. *Option*₀₆ is defined as the ratio of land owned under option to land owned outright. *Assets*₀₆ are reported in millions. *Profitability*₀₆ is defined as the ratio of net income to assets. *MarkettoBook*₀₆ is defined as the ratio of market capitalization to book value. *Tangibility*₀₆ is defined as the ratio of tangible assets to total assets. Data taken from Corelogic and Compustat.

	All Firms			Public Firms		
	mean	sd	p50	mean	sd	p50
No. Homes	71.87	503.63	9.00	4265.38	3568.27	3270.00
No. States	2.59	2.73	2.00	14.00	6.86	15.00
Geo. HHI	0.51	0.38	0.47	0.19	0.18	0.09
<i>Leverage</i> ₀₆				0.39	0.10	0.41
<i>Coverage</i> ₀₆				9.61	15.15	6.54
<i>Pct.Eq.Subs</i> ₀₆				0.00	0.00	-0.00
<i>CashtoAssets</i> ₀₆				0.05	0.06	0.04
<i>PctOption</i> ₀₆				0.85	0.39	0.76
<i>Assets</i> ₀₆				6254.60	4763.80	4559.43
<i>Profitability</i> ₀₆				0.06	0.07	0.05
<i>MarkettoBook</i> ₀₆				1.95	1.10	1.76
<i>Tangibility</i> ₀₆				0.98	0.01	0.98
Observations	2054			13		

not fallen in a significant way.¹⁰ Going into the crisis, builders carried large amounts of land on their balance sheet, not anticipating large drops in prices.¹¹ During the crisis, land prices suffered unprecedented declines, by as much as 40-60%,¹² wiping out builders' asset values. Otherwise healthy builders suddenly came close to insolvency. By 2009, 14% of public home builders operating in 2006 had been acquired or gone bankrupt. Falling asset values

¹⁰See Davis and Heathcote (2007).

¹¹Home builder annual reports.

¹²See Davis and Heathcote (2007).

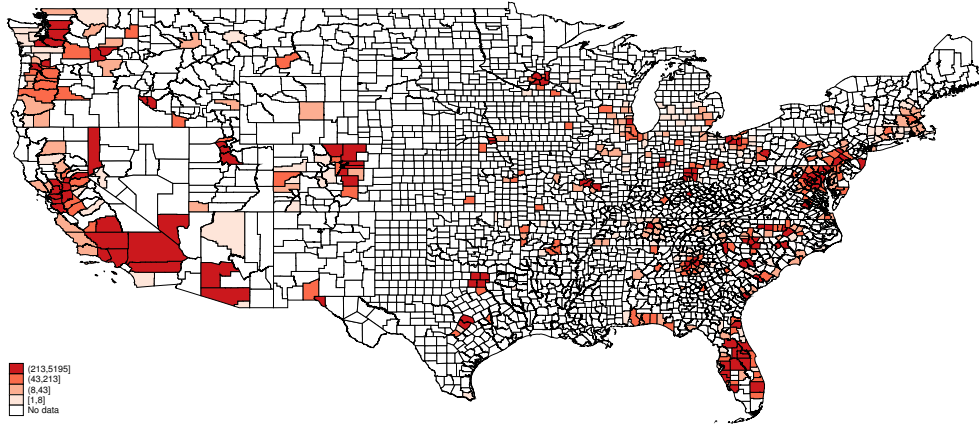


Figure 1. Builder geographic dispersion. This figure shows the geographic distribution of homes sold by the 2,054 builders in the main sample in 2009.

effectively cut off many builders from external financing during the crisis. Builders were forced to rely on internally generated funds. This led them to sell off assets at a discount.¹³

Builders explicitly discuss their difficulty in accessing financing during the crisis in their annual reports. D.R. Horton, one of the three largest public home builders in the U.S., writes in its 2009 10-k:

“During this downturn in the home building industry, we have relied principally on the positive operating cash flow we have generated to meet our working capital needs and repay outstanding indebtedness. We generated substantial operating cash flow during this time. However, the downturn and the constriction of the credit markets have reduced the other sources of liquidity available to us and increased our costs of capital.”

This is followed by a desire to sell off assets quickly:

“In light of the challenging home building market conditions experienced over the past few years, we have been operating with a primary focus to generate cash flows through reduction

¹³Home builder annual reports.

in assets.”

The credit crisis occurred simultaneously with an extreme reversal of economic fortune for builders. In the run up to 2007, builders competed with each other to buy land in hot markets like Las Vegas. The ensuing housing bust in those areas led to severe asset impairments and sell-offs for builders holding that land. The right panel of Figure 2 plots this decline, in which builder asset values peak in 2005 and then plummet between 2007 and 2010. As the annual reports make clear, builders responded to the decline in land values by rapidly selling off land to build up cash reserves. The left panel of Figure 2 plots these steep changes in builder cash: builders begin to dramatically accumulate cash beginning in 2006, with cash holdings peaking in 2009.

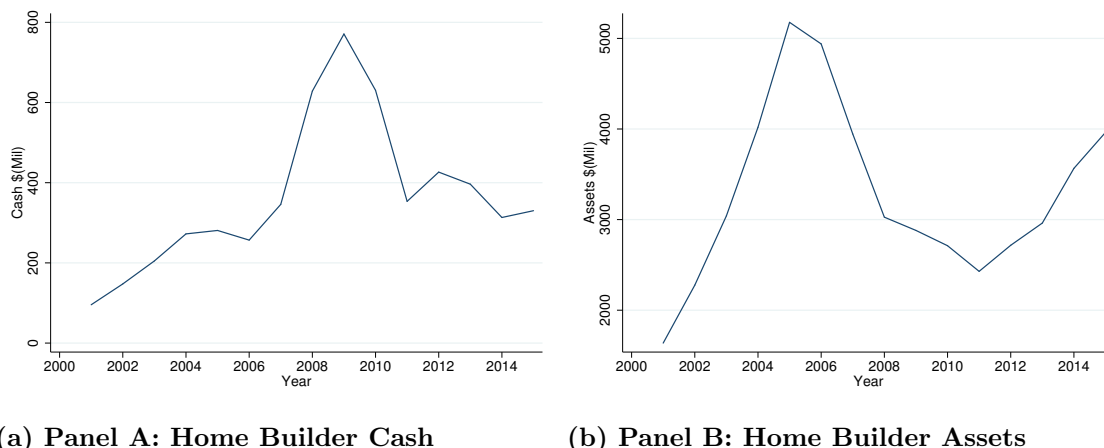


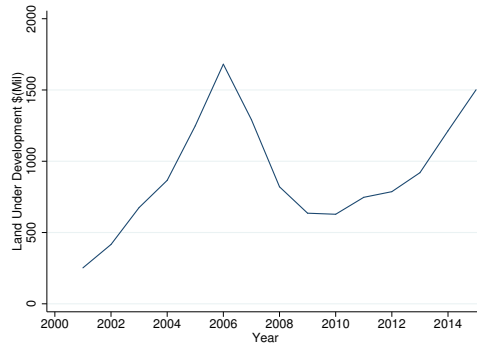
Figure 2. Home builder cash and assets. This figure plots average cash and assets between 2001 and 2015 for the group of public home builders. All data taken from Compustat.

Figure 3 illustrates how declining land values contributed to a deteriorating financial condition for builders. The upper left panel plots land under development over time. Land under development peaks in 2006 and falls by more than half in 2008. This decline should reflect three factors: builders selling off land, land value impairments, and builders choosing

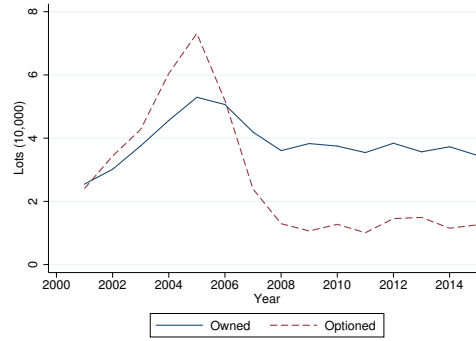
to postpone development of their holdings. Lots owned and lots optioned, (shown in the upper right panel), follow this behavior, as both lots owned and lots optioned peak in 2005 before falling sharply. Lots optioned rose more quickly in the boom and also fell more quickly in the bust than lots owned outright. Since options are easier to dispense with than land, this suggests builders may have preferred to sell off more land during the crisis than they actually did. The decline in land values led to a dramatic increase in the leverage ratio of builders from 2005 to 2009, shown in the bottom left panel of Figure 3. The increase in leverage is all the more striking because builders stopped issuing debt, as Figure 4 illustrates. The overall leverage increase implies that the decline in builder asset values overwhelmed the decline in debt issuance. Lastly, the bottom right panel of Figure 3 plots the average builder coverage ratio over time, defined as the ratio of *EBIT* to interest expense. The coverage ratio proxies for a firm’s ability to service its debt out of cash flow. Higher values indicate a healthier financial position. The average coverage ratio becomes negative in 2008, reflecting the fact that the average builder was making a loss during the crisis. Together, these figures suggest that the decline in land prices damaged builders’ finances, effectively cutting them off from external financing.

3 Identification Strategy

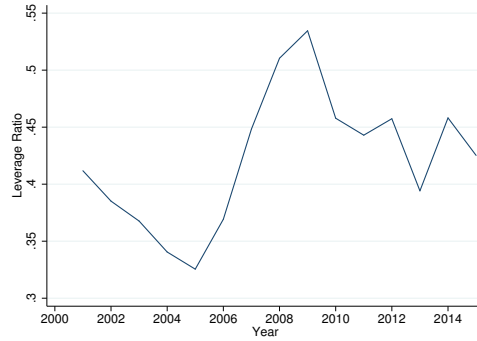
An ideal experiment to test internal capital markets would compare two identical companies, each operating multiple projects, and would randomly assign a negative revenue shock to one of the projects. Finding that the company with the shocked project diverts investment from its unshocked project to its shocked project, while the company with all unshocked projects makes no adjustment, is evidence of internal capital markets at work. Approximating this experiment in the real world is difficult due to data limitations and endogeneity concerns. First, most public firms do not report project-level investment. Therefore it is challenging to identify what constitutes an independent project within a firm, and to measure each



(a) Panel A: Land Under Development



(b) Panel B: Home Lots



(c) Panel C: Leverage Ratio



(d) Panel D: Coverage Ratio

Figure 3. Home builder land and financial ratios. These figures explore how land values deteriorated during the crisis and how this affected builder finances, for the builders who successfully match to Compustat. Panel (a) plots average land under development for public builders in millions of dollars. Panel (b) plots average number of lots owned under option and owned outright in tens of thousands of units. Lots refer to homesites. Panel (c) plots the leverage ratio for the average public builder, defined as the ratio of total debt to total assets. Panel (d) plots the coverage ratio for the average public builder, defined as the ratio of *EBIT* to interest expense. All data taken from Compustat.

project's investment and profits. Second, finding a shock which randomly affects projects within companies is difficult. When comparing two companies, one with a shocked project and one without, it is possible that the company with the shocked project is mismanaged compared to the unshocked company. If so, the mismanagement would explain both why the company's first project received a shock, and also why its second project has less investment.

Studying internal capital markets in the home builder market using a geography-based

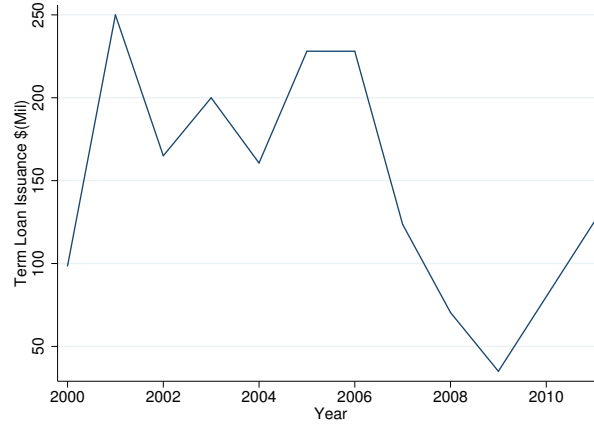


Figure 4. Home builder term loan issuance. This figure shows the term loan issuance in millions of dollars for home builders who appear in the Dealscan database. Home builders are identified by SIC code and company name.

identification addresses these concerns. Figure 5 outlines a stylized example of my research design. In this example, I compare two companies, A and B, selling homes in three counties, 1, 2, and 3. Builder A builds homes in counties 1 and 3 and Builder B builds homes in counties 2 and 3. If house prices drop significantly in county 1, where Builder A has homes for sale but Builder B does not, then Builder A will have experienced a negative shock. If Builder A is constrained by its losses in county 1, it may need to raise cash quickly and therefore may choose to sell its homes in the healthy county 3 quickly and therefore at a discount. By comparing house prices in county 3, where both A and B sell homes but which has no house price shock, I can identify whether or not Builder A spread the county 1 shock to its healthy county 3 project via internal capital markets.

I am able to use local house prices to approximate project profits thanks to characteristics of home building inventory. To illustrate this, consider an industry where prices do not proxy for profits, such as pencil manufacturers operating in multiple regions. A shock to the price of pencils in one region would not necessarily reduce the profits of the pencil manufacturer, because the firm can scale down production of pencils in the shocked region and transport existing pencils to areas with higher prices. In contrast, home building inventory is immobile

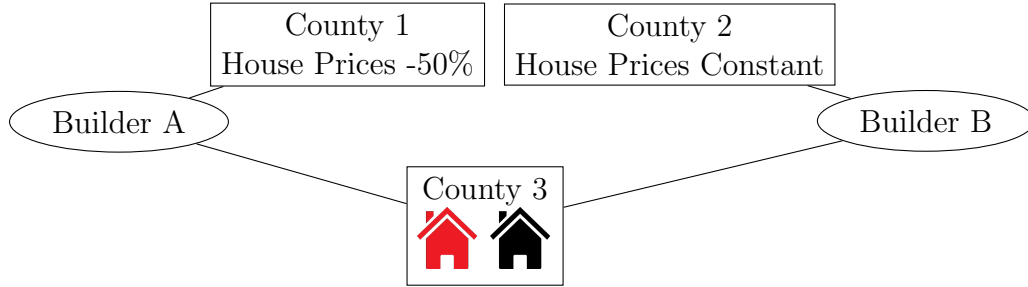


Figure 5. Example of empirical strategy. This figure illustrates my empirical strategy. Builder A sells homes in County 1 and County 3. Builder B sells homes in County 2 and County 3. House prices decline 50% in County 1 and remain constant in County 2. Builder A loses money on homes in County 1, and subsequently cuts prices in County 3, relative to Builder B's prices, in order to make sales more quickly.

and requires high upfront investment. Builders also have long operating cycles — it takes between three to five years to purchase a parcel of land, develop it, and build and sell homes. As a result, if local house prices fall steeply below what was expected when the homes were first developed, builders will be unable to recoup costs on production or to transfer inventory to areas with higher demand, causing their profits to fall. These unique features of home building inventory allow me to capture a project's profits using local house prices.

A central threat to this strategy is the possibility that builders serve different clienteles and that these clienteles respond differently to a common regional house price shock. By themselves, common regional housing shocks do not threaten the design because I compare builder home sales to other builder home sales in the same area. If there were common regional shocks, then all builders in an area would be shocked together and I should find no effect. Indeed, common regional house price shocks only pose a problem insofar as builders also serve different economic groups, and these groups respond differently to the common regional shock. As an example, suppose that builder A builds homes for white collar workers whereas builder B builds homes for blue collar workers. Additionally, suppose there is a common regional shock, and that white collar workers are much less affected by the shock than blue collar workers. Then the prices of Builder B's homes may fall relative to Builder

A's, because Builder B's clients, responding to the common shock, decrease their demand for homes whereas Builder A's clients are unaffected and their demand remains constant.

To address this problem, my analysis will exploit the rich geographic and structural detail in the Corelogic housing transactions dataset.¹⁴ I restrict to home sales made in 2009 and use zip code fixed effects to compare homes sold within the same zip code and year. I also control for observables of the home, such as square footage and bathrooms.¹⁵ It is unlikely that structurally similar homes, on the market in the same zip code and in the same year, sell to different classes of customer.

I also address this problem by testing a specification which makes it less likely that a builder's shock is common to all regions. To do this, I calculate a builder's shock using only geographically distant counties. In particular, in robustness checks I generate results in which a builder j 's county k -specific shock is calculated excluding house price changes occurring in counties in the same state as county k . This analysis excludes builders operating in multiple counties within a single state, and therefore the sample size falls. Despite the smaller number of observations, the results are similar when using this more geographically distinct definition of a builder's exposure to other regions.

Of course, the decision of where to initially build developments is not randomly assigned. Builders choose locations based on proximity to headquarters, projections for income and population growth, and local land use regulations. The validity of my analysis rests on the assumption that builders' decisions to build in certain states during the housing boom period do not correlate with their potential pricing in 2009, conditional on physical and geographic characteristics of homes. In robustness checks I test the validity of this assumption by showing that exposed and unexposed builders' pricing follow parallel trends before the crisis.

Another potential threat is the possibility that builder geographic networks overlap with

¹⁴I describe the Corelogic dataset in detail in Section 4.

¹⁵In robustness checks I control for zip code fixed effects interacted with home characteristics, to allow the effect of home quality to vary by zip code, and find the results do not change.

networks of other agents, such as lenders, who may also spread shocks across geography (Mondragon, 2018; Gilje et al., 2016; Cortés and Strahan, 2017). I address this threat in my design because I compare homes selling within the same zipcode and year. If a lender experiences losses in a housing bust area and transmits those losses to healthy areas by cutting lending, then shocked and non-shocked builders in the healthy area should be equally affected; a credit shock common to an entire zipcode cannot explain differential pricing between builders within the same zipcode.

4 Data and Summary Statistics

For my analysis I merge home sales transactions to home builders' finances and home listing records. This section discusses the merging of the data and the construction of the variables used in the paper.

My main source of data is the tax and deed databases from Corelogic. Corelogic is a private company specializing in real estate data; they compile public records of housing transactions and property tax assessments from U.S. county recorder offices. Corelogic's deed database records, for each house purchase, the seller name, buyer name, and detailed address information. The Corelogic tax database consists of tax assessments made against homes; these include information on home quality such as repairs and additions, as well as a variety of details on homes' structural characteristics. I merge the home purchase information from the deed database to the house characteristics' information in the tax database to create a dataset of housing transactions with physical characteristics of homes.

Next, I impose a number of filters on the data in order to create a sample representative of the U.S. new home market.¹⁶ First, I restrict to arms length transactions only. This

¹⁶Builder inventory mostly consists of homes and land lots. When builders are in distress, they may sell off land, in addition to homes, at a discount to raise cash quickly. When builders are in distress, the tendency to make discounted sales may be stronger for land than for homes. To see why, recall that if a builder cuts prices on homes today, this will adversely impact the prices of homes he sells in the future, because homes

excludes, for example, home sales made between family members or spouses, which may have distorted pricing. I further restrict to single family, condominium, and duplex homes. I exclude foreclosure sales and any transactions made against the home (such as refis or HELOCs), which do not represent a house purchase. I identify unique homes using the Assessor’s Parcel Number (APN) variable, the APN sequence number, and county code. The APN variable is created by the county recorder to identify unique homes. The APN sequence number is an additional county variable used to ensure a home’s uniqueness in conjunction with the APN variable. I then drop duplicate sales, in which the seller, buyer, APN identifier, APN sequence number, county code, and sale amount are the same.

Within this sample of arms length transactions, I identify a subsample of sales of newly constructed homes. I first restrict to homes built after 2000, to ensure the homes are in fact recently built. This sample includes first as well as resales of new homes; I then restrict to only the first sales of new homes.¹⁷ To validate my identification of new home sales, I compare my data to new housing permits from the Census in Appendix Figure 10. I next clean the seller name field using various string matching algorithms. String cleaning methods are not sufficient to completely group homes to builders however, because several large builders sell homes under subsidiary name brands. To ensure that I group together homes sold by the same company but under different brand names, I manually match subsidiary builder names to parent builder names for the public builders and largest private builders. I validate my assignment of homes to builders using industry data in Appendix Figure 11.

To focus on home builders of reasonable size, I remove builders who sell no more than two homes per year. To focus on builders with sufficient geographic dispersion, I require that builders sell homes in more than one county. These restrictions narrow the sample to 98,151

are priced off sales of comparable homes. This pricing effect is not at play for land sales, which suggests constrained builders have more of an incentive to cut land as opposed to home prices. Unfortunately, detailed land sale data is not available in Corelogic.

¹⁷I use the APN variable to group together sales of the same home over time. Within the resulting panels, I classify the first transaction made against the home as the new home purchase.

home sales, corresponding to approximately 25% of new homes sales made in the U.S. in 2009. These home sales are made by a total of 2,054 unique builders.

Table II reports summary statistics of the homes sold in this sample. The rich housing characteristics that Corelogic provides, such as number of bathrooms and square footage, go a long way towards determining the price of a home, and therefore are very useful controls for home quality. The average home in my sample sells for \$263,228 in 2009 dollars; for the subset of homes sold by public builders, the mean home sells for \$260,942. 92% of homes in the sample are single family as opposed to condominiums. Large public builders often have affiliated financing arms that offer mortgages to their customers. In 2009, builder mortgage arms financed 32% of home sales in my sample. Corelogic reports additional controls, such as fireplace type, roof type, and condition type, but these variables are not populated for a large fraction of homes. Including all variables makes the sample size drop significantly, so I do not use them in the main specification. Nonetheless, I show in robustness checks that the results remain similar when these variables are included.

I use the updated seller name field to merge builder homes to builder financial information from Compustat, Dealscan, and SDC Platinum. I obtain from Compustat builder financial information as well as variables specific to home builders, such as lots owned, lots owned under option, land under development, and equity in unconsolidated subsidiaries. I use Compustat to construct the leverage ratio of a firm, which I define as the ratio of total debt to assets. I also use Compustat to construct a builder's coverage ratio, defined as the ratio of EBIT to interest expense. I am able to obtain financial information from Compustat for 33 home builders over the period 2001-2015. However, in 2009, only 13 builders report finances in Compustat. I use Dealscan to obtain syndicated bank loan issuances for both public and large private home builders. I use SDC Platinum to obtain information on public bond issuances of builders. Lastly, I use the Zillow House Price Index for county level house prices.

For time-to-sale information, I use Corelogic's Multiple Listing Service (MLS) dataset,

Table II
Summary Statistics of Homes Sold

This table reports descriptive statistics of the homes sold by builders in my sample in 2009. Condo equals one if the home is a condominium, zero otherwise. Single Family equals one if the home sold is single family, zero otherwise. Builder Mortgage equals one if the home sold is financed with a mortgage provided by the builder of the home, zero otherwise. Data taken from Corelogic.

	All Firms			Public Firms		
	mean	sd	p50	mean	sd	p50
Sale Price	263227.59	166062.74	224000.00	260942.40	139625.83	227607.00
Sq. Ft.	2328.86	898.29	2126.00	2297.37	844.45	2109.00
No. Baths	2.93	0.95	3.00	2.95	1.06	3.00
Rooms	7.17	2.05	7.00	7.02	1.98	7.00
Condo	0.08	0.27	0.00	0.09	0.29	0.00
Duplex	0.00	0.00	0.00	0.00	0.00	0.00
Single Family	0.92	0.27	1.00	0.91	0.29	1.00
Mortgage Term	26.74	9.07	30.00	26.91	8.95	30.00
Builder Mortgage	0.32	0.47	0.00	0.59	0.49	1.00
Observations	98151			40186		

which has detailed records on home listings as reported by real estate agencies. The data includes the original list date of the home, the closing date and sale price, whether the listing was removed or closed, and a host of additional characteristics such as realtor name and a description of the listing. I merge the dataset of builder home sales in 2009 to the MLS dataset using the APN identifier and county code of the home. I drop listings that take place after the recorded sale of the builder transaction, to avoid listings related to the resale of the new home. I also drop duplicate listings and any listings before January 1, 2009. I define the original list date of a home after taking into account cancellations and expirations of listings that occurred before the listing tied to its 2009 sale. Finally, I use the original list date and close date to construct a measure of a home's time on the market.

Table III reports summary statistics on builder listings. Each observation represents a builder home sale matched to listings record. Approximately one-quarter of builder home sales in the main estimation sample match to a listing record. Builders sell homes through

their own offices within a development and advertise homes by listings on their websites, often not using realtors. As a result, realtors often miss builder listings in MLS, leading to the relatively low match rate between builder homes and listings. The average builder home sells approximately six months after its original listing, and homes sold by public builders sell slightly faster. Prices and home characteristics within the sample of homes that have a listing record are similar to the prices and characteristics of homes in the larger estimation sample described in Table II.

Table III
Summary Statistics of Home Listings

This table reports descriptive statistics of the listings of homes sold by builders in my sample in 2009. Condo equals one if the home is a condominium, zero otherwise. Single Family equals one if the home sold is single family, zero otherwise. Time on the market is defined as the difference between listing date and closing date. Data taken from Corelogic.

	All Firms			Public Firms		
	mean	sd	p50	mean	sd	p50
Listing Time (Days)	166.24	145.31	127.00	124.07	99.80	100.00
Sale Price	271524.17	159627.64	233025.00	265647.25	132711.53	235000.00
Sq. Ft.	2449.48	954.21	2257.00	2429.00	895.20	2268.00
No. Baths	2.99	1.09	3.00	3.01	1.44	3.00
Condo	0.05	0.22	0.00	0.07	0.25	0.00
Duplex	0.00	0.00	0.00	0.00	0.00	0.00
Single Family	0.95	0.23	1.00	0.93	0.25	1.00
Observations	23800			7053		

5 Empirical Analysis & Results

5.1 Empirical Specification

My empirical strategy analyzes the effect of builder exposure to shocked regions on the prices of builder homes in unshocked regions. I begin by constructing a measure of a builder's

exposure to house price changes in distant counties in 2009.¹⁸ Suppose a builder j operates in counties $1, \dots, K$ in 2006. The shock to builder j , in month t in 2009, in county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties $1, \dots, K$ the builder has homes in, excluding county k . The change in house prices in a county is calculated using Zillow. The weights are the fraction of the number of homes builder j has sold in 2006 in a given county r , over the total number of homes builder j sold in 2006.

$$\omega_{06,r,j} = \frac{No.homes_{06,j,r}}{No.homes_{06,j}} \quad (1)$$

A negative shock indicates that a builder has recently sold a large proportion of her available homes in areas where prices fell, and consequently is likely to have suffered losses.

The main specification is below:

$$Log(SalePrice_{i,t,j,k,09}) = \beta_1 \sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09} + \beta_2 HP_{t,k} + \beta_3 X_i + \gamma_{s(i)} + \varepsilon_{i,t,j,k} \quad (2)$$

That is, I regress the log sale price of house i , sold in month t in 2009, in county k , by builder j , on builder j 's shock measure, which is calculated excluding house prices in county k .¹⁹ ²⁰ For brevity, I denote the shock measure, $\sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09}$, as $\overline{\Delta HP}_{j,06-09}$. I include controls $HP_{t,k}$ for log county level house prices each month.²¹ All specifications also include

¹⁸In robustness exercises I calculate a builder's exposure to distant house price changes at the zip code level. Table XIX in the Appendix reports estimates using this measure, which are similar to using exposure calculated at the county level.

¹⁹To focus on geographically very distinct counties, in robustness checks I generate results in which a builder j 's county k -specific shock is calculated excluding house price changes occurring in the same state as county k .

²⁰In Equation 2 the outcome variable, house prices in 2009, overlaps with the final year of the shock measure, defined over 2006 to 2009, leaving open the possibility of reverse causality. I address this concern in Appendix Section 11.6 by re-estimating Equation 2 using house prices in 2010 as the outcome variable.

²¹To further control for local economic conditions, I also control for the change in the log of county level house prices between 2006 and 2009. See Table XVIII of the Appendix.

zip code fixed effects, $\gamma_{s(i)}$. Since I evaluate the effect only in 2009, zip code fixed effects are equivalent to zip code by year fixed effects. This specification allows me to compare sales of homes within a narrow geography and small time frame. Controls X_i include variables describing the characteristics of the house i , including: number of bathrooms, square footage, and property type (i.e., single family home, condo, or duplex). The geography fixed effects coupled with the vector of structural controls go a long way towards fully describing the price of the home. Standard errors are clustered at the county level throughout. In robustness exercises in Appendix Section 11.5 I cluster at the builder level and find that the results are similar.²²

Before reviewing the results, I summarize the threats to validity for the design. First, it is possible that the shock metric I define may not completely capture builder exposure to ailing markets. I define a builder's exposure to a region according to the number of homes a builder sells there in 2006. However, if homes sold does not proxy well for inventory, then I could mis-measure the shock. For example, if a builder has many homes on the market in Las Vegas during the housing bust, she may in fact sell very few of those homes, because demand has dried up. This builder's asset values would have indeed dropped, but the builder's shock would not fall because the shock is calculated off of homes sold, not off of unsold inventory. This will introduce observations into the analysis which have an incorrectly small shock value and a large price response, which should bias the result downwards.

A related problem is the possibility that multiple county builders respond differently to common regional shocks than single county builders. A single county builder has zero exposure to other counties, and therefore will always have a shock of zero. During the crisis, large multiple county builders, having at least some exposure to bust states, would often have negative shocks. As a result, the shock could correlate with builder dispersion and hence with

²²Equation 2 defines the outcome variable, house prices, in levels. A specification in levels can produce bias if the outcome variable exhibits autocorrelation. To address this possibility, in the Appendix I estimate a specification in first differences and find the results remain similar.

builder size. If large builders happen to respond differently to common shocks than small builders, then any effect found could be due to builder size rather than to internal capital markets. To address this concern, I restrict the sample to homes sold by large, multiple county builders.

5.2 Results

Table IV presents results from Equation 2. β_1 from Equation 2 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. All specifications include zip code fixed effects and log county level monthly house prices. The sample period corresponds to 2009, and the shock is calculated over 2006-2009. Interpreting the coefficient from column 1, I find that builders exposed to a negative 10% shock, (roughly one standard deviation of the shock), sell homes for roughly 4% less than unexposed peers in 2009. As I add controls to this specification, namely for square footage, bathrooms, and property type, the coefficient falls somewhat in magnitude and remains stable in significance. In the most restrictive specification in column 4, the coefficient implies that builders exposed to a negative 10% shock sell homes for 2.2% less than unexposed peers. In columns 5 and 6 I restrict to the subset of homes sold by public builders. In this smaller sample the standard errors increase but the effect remains. The fact that the coefficient declines when adding property-specific controls suggests that without the rich housing characteristics, I would likely be picking up clientele differences between builders in addition to internal capital markets behavior.²³

These results indicate that constrained builders cut inventory prices. Prior work by Chevalier (1995) shows an opposite result to mine: in the supermarket industry, constrained firms raise prices of inventory in order to access cash flow more quickly. My result differs

²³Recall that Corelogic reports additional controls, such as fireplace type, roof type, and condition type, but that these variables are missing for a large fraction of homes. Including all variables makes the sample size drop significantly, so I do not use them in Table IV. I show in robustness checks that the main effects remain similar with their inclusion.

Table IV
House Prices and Builders' Exposure to Other Markets

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms				Public Only	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\Delta HP}_{j,06-09}$	0.401*** (0.0834)	0.226*** (0.0371)	0.226*** (0.0371)	0.218*** (0.0373)	0.569* (0.225)	0.236* (0.120)
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes	No	Yes
Baths	No	No	Yes	Yes	No	Yes
Prop. Type FE	No	No	No	Yes	No	Yes
R^2	0.630	0.813	0.813	0.817	0.729	0.879
N	97522	97522	97522	97522	40077	40077

from hers because the nature of supermarkets differs from that of home building. The two industries have different methods of accessing cash flow quickly. A supermarket generates cash in the short-run by raising prices on its goods. This is costly in the long-run because higher prices today lead to customers over time switching to competitors, resulting in a lower market share in the future. In contrast, home builders have a weaker incentive to grow market share by cutting prices, because home builders compete with large numbers of resale homes. Instead, a home builder cuts prices on homes in order to sell them more quickly and thereby generate cash quickly. My results suggest that the effect found by Chevalier (1995) may change depending on the degree of concentration in an industry.²⁴

²⁴Gilchrist et al. (2017) find evidence in line with Chevalier (1995) using goods underlying the PPI.

The granular housing controls in Equation 2 make it unlikely that shocked builders build homes of lower quality than unshocked builders, which would explain the result in place of an internal capital markets mechanism. However, it is still possible that there is some unobserved difference in the quality of homes between shocked and unshocked builders that is not picked up by the controls. If so, then a builder’s shock should also predict prices before the crisis. To test this possibility, I run a placebo test in which I evaluate the effect of the shock in all years between 2000 and 2014, not just in 2009 as in Equation 2. Equation 3 defines this placebo specification: now the sample includes first sales of all new homes sold between 2000 and 2014.

$$\begin{aligned} \text{Log}(\text{SalePrice}_{i,t,j,k}) = & \beta_1 \overline{\Delta HP}_{j,06-09} + \sum_r^{2014} \beta_r \overline{\Delta HP}_{j,06-09} * \delta_r + \\ & \beta_2 HP_{t,k} + \beta_3 X_i + \gamma_{s(i)} + \delta_y + \varepsilon_{i,t,j,k} \end{aligned} \quad (3)$$

I regress the log sale price of house i , sold in month t , in county k , by builder j , on builder j ’s shock measure, interacted with dummies for each year between 2000 and 2014, denoted by δ_y . I continue to define the shock measure over the 2006-2009 horizon as $\overline{\Delta HP}_{j,06-09}$. I plot the coefficients of the shock interacted with the year dummies in Figure 6. The figure indicates that the shock becomes significant only beginning in 2007, and decays in size as the crisis unwinds. I find no evidence of pre-existing differences between shocked and unshocked builders before the crisis.

6 Mechanism

6.1 Financial Constraints

The results so far suggest that builders experiencing larger losses on homes sold in distant counties are more likely to sell homes in unaffected areas at a discount. To interpret this

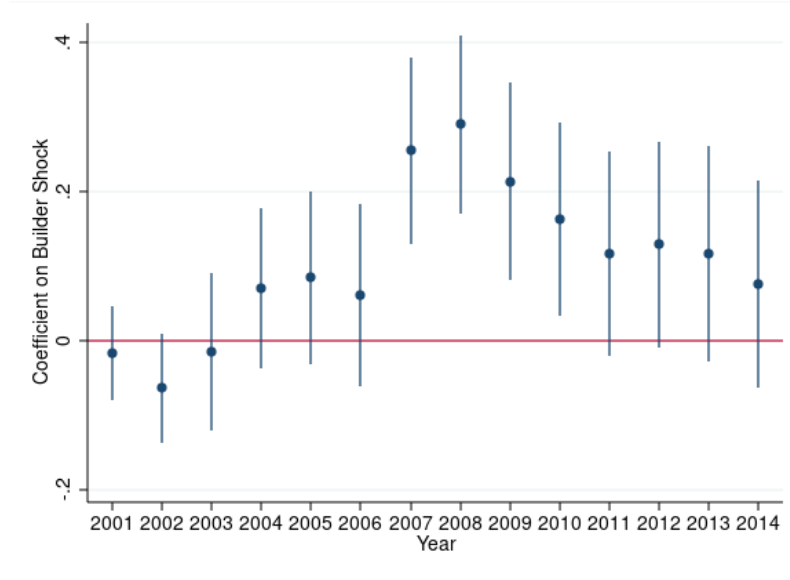


Figure 6. Effect of home builder shock by year. This figure tests for a pre-existing difference in price between shocked and unshocked builders. A regression of log sale prices on a builder's shock measure interacted with a series of year dummies produce the estimates. A builder's shock measure captures the exposure of a builder to other markets. The sample period spans 2000 to 2014. The base year is 2000 and is omitted. The 95% confidence intervals are calculated from standard errors clustered at the county level. The regression also includes zip code fixed effects as well as controls for property characteristics.

finding as evidence of internal capital markets, I need to show first, that the tendency to spread shocks is stronger for more financially constrained firms, and second, that this effect only occurs during periods of costly external finance.

I therefore investigate whether the effect varies with builder financial constraints. Measuring a firm's ability to obtain a loan is not straightforward. Previous corporate finance literature often uses the leverage ratio as a proxy for financial constraints. One could imagine, however, that having a large debt load suggests that banks are very willing to lend to the firm, and therefore that the firm would easily be able to obtain additional financing. For any given proxy, one can argue that it does not capture true financial constraints. To get around this, I use a host of different proxies for financial constraint, some from the corporate finance literature and some unique to home builders. If the tendency to spread a shock across projects is always stronger for firms with higher proxies for constraints, it becomes

more likely that the mechanism explaining the result is financial constraints.

Table V reports heterogeneous responses along various proxies for financial constraints. I have financial information only for public home builders, so I restrict this analysis to the public firms. Columns (1) to (5) report results from regressing log house prices on the builder's shock measure, calculated as in Equation 2, where the shock is interacted with different proxies for builder financial constraints. The diagonals highlighted in red on the table report the coefficient from that interaction term separately for the five different proxies. The first row of the table reports the coefficient on the uninteracted shock term. Zip code fixed effects, the log of the county level house price index, and the builder's log assets are included as controls in each specification.

The first column of Table V reports the coefficient on the interaction between builder leverage ratio in 2006 and the shock measure. The coefficient is significant and positive, indicating that firms with higher leverage ratios going into the crisis were more likely to spread shocks across projects in 2009. Increasing leverage by one standard deviation increases the tendency to spread shocks across projects by one-third. The second column reports the coefficient on the interaction between builder coverage ratio in 2006 and the shock measure. Coverage ratio is defined as the ratio of EBIT to interest expense, and captures a firm's ability to pay its debt out of cash flow. The coefficient is significant and negative, indicating that firms with a higher coverage ratio in 2006 were less likely to spread shocks across projects in 2009. In other words, firms with less ability to service their debt were more prone to spread shocks across projects in 2009.

In column 3 of Table V I interact equity in subsidiaries with the shock measure. Equity in subsidiaries captures the extent to which a builder invested in subsidiary companies in 2006. More investment in subsidiaries could indicate more diversification, and therefore that a builder is more hedged to large swings in real estate values. The coefficient on the interaction of this variable with the shock measure is significant and negative, indicating that firms with more equity in subsidiaries as a fraction of assets in 2006 were less likely to

Table V
Heterogeneity Along Financial Constraints

This table reports heterogeneous effects of builder exposure to other markets on price along various proxies for financial constraints. Columns (1) to (5) report results from regressing log house prices on the builder's shock measure interacted with different proxies for builder financial constraints. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has homes in. The change in house prices in a county is calculated using Zillow. The weights are the ratio of the number of homes builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). The diagonals highlighted in red on the table report the coefficient from the interaction of the shock with the financial constraint proxy. The first row of the table reports the coefficient on the uninteracted shock term. Each financial constraint proxy is calculated in 2006. Leverage is defined as the ratio of total debt to total assets. Coverage is defined as the ratio of *EBIT* to interest expense. Equity in subsidiaries (*EqtySubs*.₀₆) is defined as the extent to which a builder invested in subsidiaries in 2006. *EqtySubs.Assets*₀₆ is defined as equity in subsidiaries as a fraction of assets. *Option*₀₆ is defined as the ratio of land a builder owns under options to land owned outright in 2006. Column (6) reports results from a regression in which all interaction terms are included at once. The sample is restricted to homes sold by public builders. Zip code fixed effects, the log of the county level house price index, and the builder's log assets are included as controls in each specification.

	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{\Delta HP}_{j,06-09}$	-2.044*	1.290**	0.554**	0.583**	2.234**	-4.716
	(0.954)	(0.464)	(0.184)	(0.185)	(0.793)	(3.843)
$Leverage_{06} \times \overline{\Delta HP}_{j,06-09}$	6.863*					12.39
	(2.804)					(6.822)
$Coverage_{06} \times \overline{\Delta HP}_{j,06-09}$		-0.180***				0.151
		(0.0520)				(0.196)
$EqtySubs.Assets_{06} \times \overline{\Delta HP}_{j,06-09}$			-320.1**			328.8
			(110.1)			(654.8)
$EqtySubs_{06} \times \overline{\Delta HP}_{j,06-09}$				-0.0252**		-0.0585
				(0.00927)		(0.0585)
$Pct.Option_{06} \times \overline{\Delta HP}_{j,06-09}$					-2.615***	-2.202*
					(0.772)	(1.037)
Effect at Median	0.770	0.113	0.567	0.585	0.247	NA
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Zip	Yes	Yes	Yes	Yes	Yes	Yes
County HP Index	Yes	Yes	Yes	Yes	Yes	Yes
Ln Asset	Yes	Yes	Yes	Yes	Yes	Yes
Shock	Yes	Yes	Yes	Yes	Yes	Yes
Non Inter. Var	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.725	0.724	0.725	0.725	0.720	0.731
N	43930	43930	43930	43930	36246	36246

spread shocks across projects in 2009. In other words, firms with possibly less diversification going into the crisis were more prone to spread shocks across projects in 2009. The results are similar when looking at equity in subsidiaries using levels rather than as a fraction of assets.

I next use institutional details of the home building industry to construct a constraint unique to builders. Column 5 reports the coefficient on the interaction between the ratio of land a builder owned under options to land owned outright in 2006 and the shock measure. Often, builders purchase land parcels using options, giving them the right to buy the land outright at a certain price within a given date. When land values plummeted in 2009, builders with more of their land owned via options rather than owned outright were in a stronger financial position. The coefficient on the interaction of this variable with the shock measure is significant and negative, indicating that firms more exposed to falling land values were more prone to spread shocks across projects in 2009. Column 6 reports results from a regression in which all interaction terms are included at once. Only *Option₀₆* remains significant, likely because the multicollinearity of the proxies makes identifying separate effects difficult.

The first row of the bottom panel of Table V reports the effect of the shock calculated at the median value of the financial constraint proxies. The effect of the shock at the median value is positive for every measure used, indicating that in general, builders in this group were spreading shocks across projects in 2009. For each proxy considered in Table V, builders more likely to be financially constrained according to that proxy were more likely to spread shocks across projects, evidence that the mechanism behind the effect is internal capital markets.

The results in Table V exploit heterogeneity in financial constraints within the cross section of public builders in 2009. However, there is also time series variation in financial constraints within the builder industry as a whole. During the housing boom, credit standards were loose and builders could easily obtain loans, whereas the opposite was true during the crisis. If the mechanism is internal capital markets, then in periods in which builders

could easily obtain loans, there should be no tendency for builders to spread shocks across projects. Unconstrained builders will set listing times for their homes optimally, regardless of whether they receive price shocks in distant projects. Because builders could easily obtain financing during the boom period, there should be no effect.

To test this, I shift the main specification to the boom years, 2002 to 2005. In Equation 4, I regress the log sale price of house i , sold in month t in 2005, in county k , by builder j , on builder j 's shock measure, which is calculated excluding house prices in county k .

$$\text{Log}(\text{SalePrice}_{i,t,j,k,05}) = \beta_1 \overline{\Delta HP}_{j,02-05} + \beta_2 HP_{t,k} + \beta_3 X_i + \gamma_{s(i)} + \varepsilon_{i,t,j,k} \quad (4)$$

The shock measure is calculated as in Equation 2, but over years 2002 to 2005, as opposed to over years 2006 to 2009 as in the main results. For brevity, in Equation 4, I denote the shock measure during the boom, $\sum_{r \neq k}^K \omega_{02,r,j} \Delta(HP_r)_{02-05}$, as $\overline{\Delta HP}_{j,02-05}$. Just like in Equation 2, I include controls $HP_{t,k}$ for log county level house prices each month. All specifications also include zip code fixed effects. Controls X_i include variables describing the characteristics of house i , including: number of bathrooms, square footage, and property type (i.e., single family home, condo, or duplex). Standard errors are clustered at the county level.

Table VI presents results from Equation 4. β_1 from Equation 4 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. In columns 5 and 6 I restrict to the subset of homes sold by public builders. Note the sample size is more than three times the size of the sample in Table IV, due to the fact that many more new homes are sold in 2005 than in 2009. In the first specification, the effect is insignificant and close to zero. In the specifications with housing controls, the effect is marginally significant, but not significant at the 5% level used in the rest of the analysis. Importantly, the effect is close to zero (approximately one-fifth to one-tenth the magnitude of the effect in Table IV). These results indicate that builders spread shocks across projects during the 2006-09 crisis but not during the preceding

boom. Because builders were more likely to be financially unconstrained during the boom, this finding is consistent with an internal capital markets mechanism. One threat to the design is the possibility that builders learn from house price busts in crisis areas and use this information to mark down prices in healthy regions in anticipation of the crisis spreading. However, learning should occur during both booms and busts. Since I find linkages between projects only during the crisis and not during the boom, learning cannot explain the results.

Table VI
House Prices and Builders' Exposure to Other Markets
During the Boom

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level during the boom period. The dependent variable is the log of house prices in 2005. The independent variable is the builder's exposure to house price changes in distant counties in 2005. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2002 and 2005 in all other counties the builder has homes in. The change in house prices in a county is calculated using Zillow. The weights are the ratio of the number of homes builder has sold in 2002 in a given county, over the total number of homes the builder sold in 2002 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms				Public Only	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta HP_{j,02-05}$	-0.0501 (0.0405)	-0.0424 (0.0230)	-0.0419 (0.0230)	-0.0424 (0.0229)	0.113 (0.128)	-0.00473 (0.0628)
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes	No	Yes
Baths	No	No	Yes	Yes	No	Yes
Prop. Type FE	No	No	No	Yes	No	Yes
R^2	0.687	0.833	0.833	0.835	0.773	0.886
N	299847	299847	299847	299847	150926	150926

6.2 Effect on Listing Times

I find that builders respond to a loss in one project by cutting prices in unaffected projects. For this result to imply that builders spread price shocks across projects via internal capital markets, then it should be the case that when builders cut prices they sell homes faster. In this section, I investigate whether builders experiencing negative shocks are more likely not only to cut prices but also to sell their homes more quickly.²⁵

I regress home listing times on the builder’s shock measure, calculated as in Equation 1, using the same set of controls as in Equation 2. I estimate the regression on the sample of homes that match to MLS, as described in Table III. Table VII reports coefficients on the shock measure, β_1 , along with standard errors. The first five columns of the table refer to specifications estimated over the full sample of builder home sales matched to MLS. The first four columns use time-to-sale as the outcome variable and the fifth column uses sale price as the outcome variable. The last two columns correspond to specifications restricted to the sample of homes sold by public builders: columns 6 and 7 have time-to-sale and sale price as outcome variables, respectively. All specifications include zip code by year fixed effects and log county level monthly house prices. Interpreting the coefficient from column 4, I find that builders exposed to a negative 10% shock, (roughly one standard deviation), sell homes 14 days more quickly.²⁶ ²⁷ As I add controls to the specification using the full sample for

²⁵A number of papers have shown that in general, cutting listing prices for homes results in faster times to sale (Merlo et al., 2015; Genesove and Mayer, 1994; Levitt and Syverson, 2008). Guren (2018) shows that the effect of changing a home’s listing price on its time on the market is not linear in price. In particular, the relationship between price and time on the market is strongest when the home is above average price in an area. Builder home prices will almost always be above average price due to the new conditions of builder homes, so this relationship should apply.

²⁶To validate the result that constrained builders sell homes faster in the full sample of builder sales, in Appendix Section 11.3 I show that builders with exposure to housing bust markets are more likely to sell a home in the same year it is built rather than in following years.

²⁷I also validate my results against existing relationships between time-to-sale and price for resale homes. Guren (2018) finds that raising listing price of a home by 1% makes the home sell five to six days more slowly. Interpreting the coefficient from Table IV, I find that builders with a negative shock of 4.6% cut prices by 1%. Using the listing times results in Table VII, I find that builders with a negative shock of 4.6% also sell homes 6 days more quickly, implying that when builders cut prices by 1% they sell homes 6 days

square footage, bathrooms, and property type, the coefficient remains stable in significance and magnitude. Recall that the results from Table IV imply that builders exposed to a negative 10% shock sell homes at a 2.2% discount. The coefficient in column 5 of Table VII implies a similar result, that in the smaller sample of builder homes matched to listing records, builders exposed to a negative 10% shock sell homes at a 2.1% discount.²⁸ The coefficient is not significant for the smaller, public only sample, which contains only 6,927 listings.

The results from columns 4 and 5 together indicate that builders trade off 2.1% in sale price for selling 14 days sooner, implying an annualized discount rate of 72%. For comparison, the average rate on builder debt is 14%²⁹ during the boom period. Builders issued no debt during the crisis. Builders likely only use internal financing from accelerated home sales when external financing is excessively costly. If builders relied on an internal discount rate of 72% in 2009, then the rate of external financing must have been greater than 72%, indicating that the cost of external financing between the boom and the bust at the very least quadrupled in size.

7 Heterogeneity

7.1 Time-to-Sale Sensitivity

The housing market features search frictions which produce a positive relationship between price and time-to-sale. If builders are financially constrained and need cash quickly, they

faster. Assuming symmetric responses for raising and lowering listing price on time-to-sale, the relationship I find is close to the one in Guren (2018).

²⁸The above approach uses OLS to provide evidence that the duration until a home is sold is related to a builder's exposure to other markets. OLS assumes duration times are normally distributed; however, duration data are often right skewed. I address the possibility that the normality assumption fails in Appendix Section 11.2 by instead assuming that the homes' duration times follow a Weibull distribution, which allows for fat right tails.

²⁹Source: SDC Platinum.

Table VII

Listing Time and Builders' Exposure to Other Markets

This table explores the effect of builders' exposure to other housing markets on how quickly they sell their homes, measured at the housing transaction level. The dependent variable in columns 1-4 and column 6 is a home's listing time, defined as the difference between the original list date and the sale date. The dependent variable in columns 5 and 7 is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). The sample consists of first sales of new homes occurring in 2009. All regressions are ordinary least squares (OLS) and include zip code by year fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms				Public Only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Time	Time	Time	Time	Price	Time	Price
$\Delta H\bar{P}_{j,06-09}$	146.6*** (25.45)	137.7*** (25.26)	137.6*** (25.30)	136.9*** (25.51)	0.205*** (0.0438)	-72.76 (63.69)	0.307 (0.207)
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes	Yes	Yes	Yes
Baths	No	No	Yes	Yes	Yes	Yes	Yes
Prop. Type FE	No	No	No	Yes	Yes	Yes	Yes
R^2	0.280	0.284	0.284	0.285	0.853	0.287	0.891
N	23351	23351	23351	23351	23351	6927	6927

should cut prices more in areas where this relationship is stronger, where a given price cut generates a larger decline in time-to-sale. I test this implication in this section by exploring whether builders are more likely to spread negative shocks to projects in areas where time-to-sale responds more strongly to price cuts. For this analysis I use the MLS listings data; details on the sample construction are described in Appendix Section 11.4.

To estimate the relationship between time-to-sale and price, ideally I would observe a home's "true," quality-adjusted price and then estimate how time-to-sale varies with deviations from the true value (Guren, 2018). For example, if a home is overvalued it will take

longer to sell. In practice, we do not observe a home's true value; instead I approximate true value using a hedonic regression. To capture how time-to-sale changes with price, I then estimate the relationship between the probability of sale within a given time and the difference between realized price and predicted price (the mark-up).

To generate home i 's predicted price, $\hat{p}_{i,t}$, I regress log sale price, $p_{i,t}$, on physical characteristics, X_i , and date t and county k fixed effects, $\xi_{k,t}$, in Equation 5.

$$p_{i,t} = \beta X_i + \xi_{k,t} + \epsilon_{i,t} \quad (5)$$

I formalize the relationship between time-to-sale and price following Guren (2018), modeling the probability of a home selling within 13 weeks, $d_{i,t}$, as a function of predicted mark-up and date and county fixed effects in Equation 6.

$$d_{i,t} = \rho \underbrace{(\hat{p}_{i,t} - p_{i,t})}_{\text{mark-up}} + \xi_{i,t} + \varepsilon_{i,t} \quad (6)$$

The mark-up is the residual from the hedonic regression in Equation 5. I estimate Equation 6 grouping mark-up values into bins and I plot the coefficients on each mark-up bin in Figure 7. Consistent with Guren (2018), the relationship between probability of sale and mark-up in Figure 7 is concave and for positive mark-ups the relationship is negative. When homes are overvalued, their probability of sale declines.

To identify regions where price cuts produce larger declines in time-to-sale, I generate sensitivities of time-to-sale for each county.³⁰ Next, I divide the main estimation sample into quantiles according to the county time-to-sale elasticity to price and estimate Equation 2 within each quantile. I plot the coefficient on the builder shock measure from the regression

³⁰I estimate Equation 6 within each county and define the county time-to-sale sensitivity as $\rho * (-1)$. I multiply ρ by -1 for ease of interpretation.

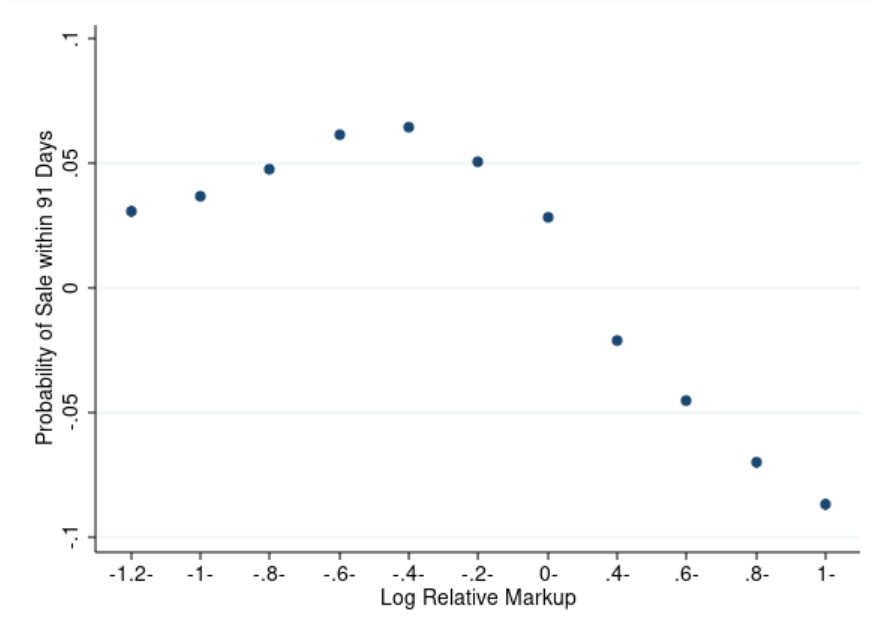


Figure 7. Probability of selling within 13 weeks and mark-up. The figure plots the coefficients on mark-up bins from a regression of probability of a home selling within 13 weeks on bins of mark-up value. Mark-up value is defined as the difference between log sale price and log predicted price, where log predicted price is generated from a regression of sale price on home characteristics and date and county fixed effects.

within each time-to-sale sensitivity quantile in Figure 8.

Figure 8 shows that builders are most likely to spread negative shocks to projects with the largest sensitivity of time-to-sale to price. Consistent with financial constraints, builders cut prices more in areas where cutting prices speeds up sales the most.

7.2 Competition

I next explore whether the effect varies with a county's level of competition. If a builder receives a negative shock in one county, she may choose to discount prices in her other projects according to those projects' competitive landscapes. Builders may choose to spread shocks to more competitive counties because builder reputation likely matters less in more competitive areas. The presence of more competitors means that via comparable pricing,

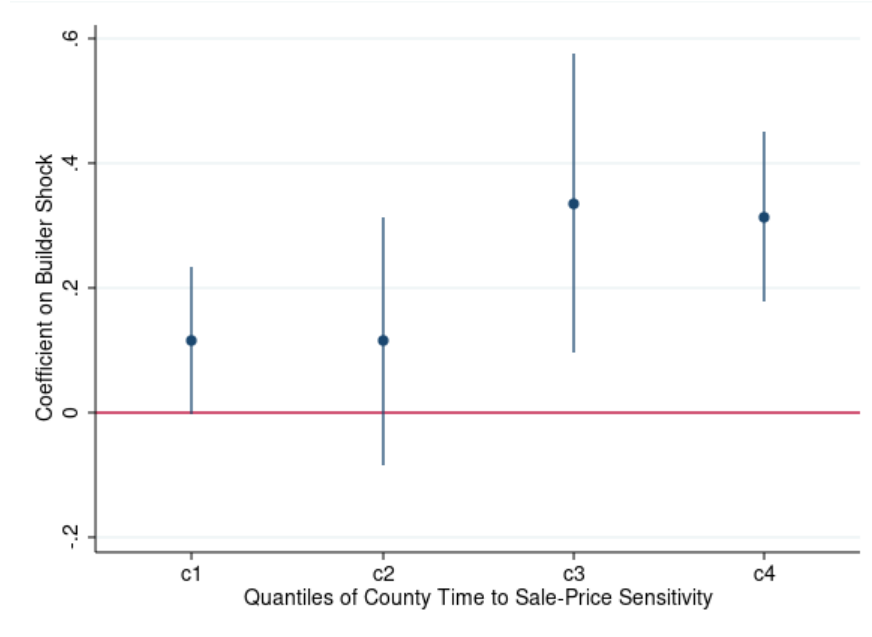


Figure 8. Heterogeneity by time-to-sale elasticity. This figure plots the effect of a builder's shock on price according to quantiles of county time-to-sale sensitivity. County time-to-sale sensitivity is defined as the absolute value of the coefficient on markup from a county-level regression of probability of sale within 13 weeks on markup. Markup is defined as the difference between log sale price and log predicted price, where log predicted price is generated from a hedonic regression described in Equation 5. A regression of log sale prices on a builder's shock is estimated separately in each quantile of county time-to-sale sensitivity and the coefficient and its confidence interval is plotted. A builder's shock measure captures the exposure of a builder to other markets. The 95% confidence intervals are calculated from standard errors clustered at the county level. The regression also includes zip code fixed effects as well as controls for property characteristics.

the prices of a builder's homes will be less tied to the past pricing of that same builder, and more tied to the past pricing of other builders. Therefore, in a competitive county, if a builder slashes prices on her homes today, it should have less effect on the prices of homes she sells in that area in the future.³¹

To test this, I first construct a measure of concentration following Scharfstein and Sunderam (2014), defined as the share of each county's market served by the top four home builders in the county. I then split the sample according to quartiles of builder concentra-

³¹Competition may proxy for market liquidity which could correlate with time-to-sale sensitivity to price. The results in this section are robust to controlling for county time-to-sale sensitivity to price as defined in Section 7.1.

tion and estimate Equation 2 separately in each quartile. The coefficient β_1 from the shock is plotted separately for each quartile in Figure 9. The effect strictly declines with county concentration. These results suggest builders do not spread a negative shock across unaffected projects equally, but rather spread shocks more to projects where their reputation matters less.

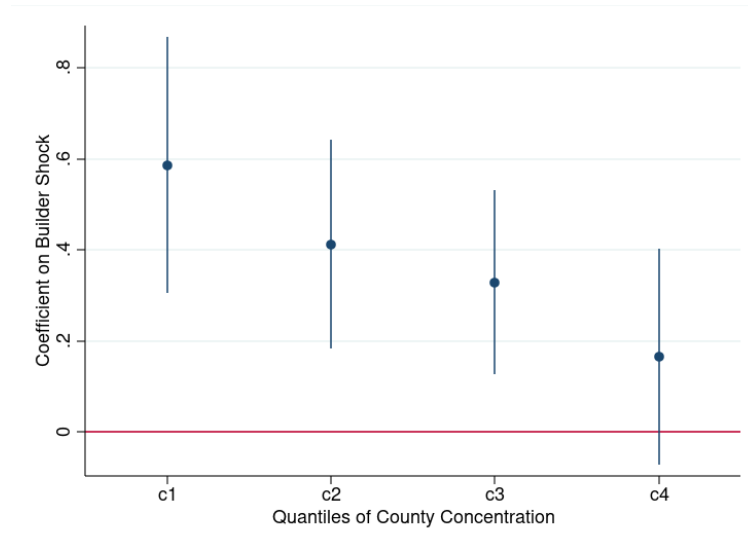


Figure 9. Heterogeneity by county concentration. This figure plots the effect of a builder’s shock on price according to quartile of county concentration. County concentration is constructed as the share of each county’s market served by the top four largest home builders in the county. A regression of log sale prices on a builder’s shock is estimated separately in each quartile and the coefficient and its confidence interval is plotted. A builder’s shock measure captures the exposure of a builder to other markets. The 95% confidence intervals are calculated from standard errors clustered at the county level. The regression also includes zip code fixed effects as well as controls for property characteristics.

8 Spillover to Nearby Homes

Previous work on foreclosures, (Campbell et al., 2011), show that when a home sells in foreclosure, the sale prices of nearby, similar homes fall. This finding suggests that when builders sell homes at a discount in a healthy county, the sale prices of nearby, similar homes

may be affected. Declines in home prices are important; Mian and Sufi (2014) provide evidence that declines in household net worth reduce consumer demand and employment. Finding that in unaffected counties, a home sold at a discount by a constrained builder causes nearby home prices to fall, suggests that builder internal networks are a channel of geographic contagion.

I test for spillover pricing between builder and resale homes in this section. To identify homes similar to builder ones, I restrict my sample to new homes, defined as those built after 2000. Recall I define a builder home sale as the first sale of a newly built home occurring in 2009. To ensure I do not include any builder homes in this analysis of resale homes, I require that the homes are first sold by a builder to a home-owner before 2008. I then restrict my sample to sales of these homes occurring in 2009. A typical home in this group is first sold from a builder to a home-owner in 2005, and then resold from the first home-owner to another home-owner in 2009. These homes should be considered comparable to builder homes, given their recent construction, but I will never count them as builder sales.

I next evaluate whether a shocked builder selling her home at a discount causes nearby resale home prices to fall. I do this by testing if the sale price of a resale house is affected by the shocks experienced by nearby builders. I define a resale home's exposure to nearby builder shocks as the weighted sum of the shocks experienced by builder homes sold in the same zip code one month earlier. The weights in the sum are the inverse of the distance between a resale house, i , and a builder house, j , referred to as $distance_{i,j}$. Suppose a resale home i is sold in zip code s in month t , and there are J_{t-1} total builder homes sold in zip code s in month $t - 1$. Then the aggregated shock for resale home i in zip code s , sold in month t , is:

$$Aggr.Shock_{i,t,s,k,09} = \sum_{j=1}^{J_{t-1}} \frac{1}{distance_{i,j}} * shock_{\sim k,j} \quad (7)$$

Where $shock_{\sim k,j}$ is a builder's shock, $\sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09}$, or, $\overline{\Delta HP}_{j,06-09}$, as defined earlier in Equation 2. Intuitively, a shocked builder selling his house j at a discount in zip code s , in month $t - 1$, will have a bigger effect on the sale price of house i in zip code s , sold in month t , if the builder home j is closer to house i .

Equation 8 describes the main spillover specification.

$$\begin{aligned} LogSalePrice_{i,t,s,k,09} = & \beta_1 \sum_{j=1}^{J_{t-1}} \frac{1}{distance_{i,j}} * shock_{\sim k,j} + \beta_2 X_i + \\ & HP_{t,k} + \gamma_{s(i)} + \delta_t + \gamma_{s(i)} * \delta_t + \varepsilon_{i,t,s,k} \end{aligned} \quad (8)$$

I regress the log sale price of resale house i , sold in month t in 2009, in zip code s , in county k , on home i 's exposure to nearby builder shocks, defined in Equation 7. I include controls $HP_{t,k}$ for log county level house prices, as well as zip code fixed effects $\gamma_{s(i)}$, and zip code by year by month fixed effects, $\gamma_{s(i)} * \delta_t$. Controls X_i include variables describing the characteristics of the house i .

Table VIII reports the results from Equation 8 in which the outcome variable is now prices of resale homes. β_1 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. All specifications include zip code fixed effects and log county level monthly house prices. Interpreting the coefficient from column 5, a home sale by a builder experiencing a negative 10% shock causes the prices of resale homes within a 0.05 mi radius to fall by 1%. To put this result in perspective, Campbell et al. (2011) find that a home sold in foreclosure causes the prices of homes within a 0.05 mi radius to fall by 1%. When constrained builders sell homes in healthy markets at a discount, nearby home prices fall. This result suggests that builder internal capital markets serve as a channel of geographic contagion of negative economic shocks.³²

³²Builder homes only make up a small fraction of total home sales in a county, so builders' influence on

Table VIII
Spillover to Nearby Homes

This table explores the effect of builders' shocks on the prices of nearby resale homes. The dependent variable is the log of resale house prices in 2009. The independent variable is a resale home's exposure to nearby builder shocks. This exposure is defined as the weighted sum of the shocks experienced by builder homes sold in the same zip code, one month before the resale home sale. The weights in the sum are the inverse of the distance between the resale house and the builder house. All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms				
	(1)	(2)	(3)	(4)	(5)
Aggr. Shock	0.00906*** (0.00226)	0.00485** (0.00152)	0.00514*** (0.00154)	0.00434** (0.00160)	0.00491** (0.00150)
Zip FE	Yes	Yes	Yes	Yes	Yes
Yr x Mo. x Zip FE	Yes	Yes	Yes	No	Yes
County HP	Yes	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes	Yes
Baths	No	No	Yes	Yes	Yes
Prop. Type	No	No	No	Yes	Yes
R^2	0.606	0.750	0.753	0.699	0.755
N	192194	192194	192194	211163	192194

9 Additional Robustness

9.1 Comparable Pricing: Narrow Time Window of Comparison

Comparable pricing is an important feature of the housing market. Comparable pricing refers to a home's sale price depending on the past sales of nearby, similar homes. Campbell et al. (2011) show empirical evidence for comparable pricing: homes selling in foreclosure tend to decrease the sale prices of nearby homes. Comparable pricing likely attenuates the effect I find. My identification strategy compares sale prices of homes sold within a narrow geography and time frame, so as to match shocked and unshocked builders as closely as county-level prices is limited.

possible. At the same time, homes sold within the same narrow geography and time frame are also more likely to be priced off of each other. A shocked builder slashing prices on his homes in one zip code will cause other builder homes in that same zip code to decline in price. Comparable pricing of homes should therefore attenuate the effect.

To test that my effect would be stronger in the absence of comparable pricing, I narrow the time fixed effects in Equation 2 from one year to one month. Comparable pricing is less likely to have an effect in more narrow time frames because information on prices takes time to disperse. In the extreme, if two homes sell on the same day, then neither home sale should contaminate the price of the other.

Table IX reports results from adding zip code by year month fixed effects to Equation 2. β_1 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. All specifications include zip code by year month fixed effects and log county level monthly house prices. The sample period corresponds to 2009, and the shock is calculated over 2006-2009. Across every specification, the coefficient on β_1 is larger than in the specifications using only zip code by year fixed effects. This result suggests that comparable pricing likely has attenuated the effect in Table IV.

9.2 Alternative Specifications

9.2.1 Additional Controls

The validity of my analysis rests on the assumption that shocked and unshocked builders do not sell homes to different clienteles. If builders did sell to different socio-economic groups, then there would be a difference in the luxury or quality of the homes builders sell. To test the possibility that builders sell to different socio-economic groups, I add a host of additional controls for housing quality to Equation 2, such as roof type, fireplace type, and condition type. I do not include them in my main results in Table IV, because these variables are

Table IX
**Robustness: Narrow Time Frame of
Comparison**

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level and within a narrower time frame than the main results. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code by year month fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\Delta HP_{j,06-09}$	0.418*** (0.0942)	0.238*** (0.0394)	0.237*** (0.0395)	0.233*** (0.0394)
Yr. X Mo. x Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.684	0.848	0.848	0.851
N	91357	91357	91357	91357

missing for a large number of observations. Table X reports the results. Each column of the table corresponds to a specification with a different set of housing characteristic controls. Despite using a much smaller sample, the results remain similar when adding controls for roof type, fireplace type, and condition type.

To allow the effect of quality on price to vary by zipcode, I add interactions of zipcode fixed effects and home quality variables to the main specification in Table XI. I find the results remain robust using these even more granular controls, indicating that differences in

Table X
Robustness: Include Additional Controls

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level. This specification includes housing controls not included in the main results. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	0.220** (0.0789)	0.203** (0.0714)	0.203** (0.0705)	0.203** (0.0705)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	Yes	Yes	Yes	Yes
Baths	Yes	Yes	Yes	Yes
Prop. Type FE	Yes	Yes	Yes	Yes
Roof Type	No	Yes	Yes	Yes
Fireplace	No	No	Yes	Yes
Condition	No	No	No	Yes
R^2	0.812	0.815	0.818	0.818
N	8306	8306	8306	8306

home quality between builders, which could correlate with differences in builder clientele, do not drive the main results.

Table XI
Robustness: Quality by Zipcode FE

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level. This specification includes housing controls not included in the main results. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	0.218*** (0.0373)	0.201*** (0.0321)	0.196*** (0.0333)	0.198*** (0.0334)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	Yes	Yes	Yes	Yes
Baths	Yes	Yes	Yes	Yes
Prop. Type FE	Yes	Yes	Yes	Yes
Zip x Sq. Ft. FE	No	Yes	Yes	Yes
Zip x Baths FE	No	No	Yes	Yes
Zip x Prop. Type FE	No	No	No	Yes
R^2	0.817	0.849	0.859	0.862
N	97522	97522	97522	97413

9.2.2 Builder Exposure Using Geographically Distant Counties

As described above, a key threat to my design is the possibility that builders serve different clienteles, and that these clienteles respond differently to common regional house price shocks. I addressed this problem in the previous sections by including controls for home quality and by comparing homes sold within a narrow geography and time frame. Here, I address this problem by estimating a specification which makes it less likely that a builder's shock is

common to all regions. Specifically, I calculate a builder's shock using only geographically distant counties. I define a builder j 's county k -specific shock excluding house price changes occurring in counties in the same state as county k . In Table XII I report results from Equation 2, in which builder exposure to other markets has been modified to mean exposure only to markets in other states. Each column of the table corresponds to a specification with a different set of housing characteristic controls.

Table XII
Robustness: Geographically Distant
Counties

This table explores the effect of builders' exposure to very distant housing markets on their pricing, measured at the housing transaction level. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in, excluding counties in the same state as county k . The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\Delta HP_{j,06-09}$	0.440*** (0.0825)	0.211*** (0.0398)	0.211*** (0.0398)	0.206*** (0.0406)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.643	0.823	0.823	0.826
N	84647	84647	84647	84647

This analysis will exclude builders operating in multiple counties within a single state, and therefore the sample size falls. Nonetheless, the results remain similar to using this more geographically distinct definition of a builder’s exposure to other regions. Interpreting the coefficient from column 4, I find that a builder exposed to a 10% decline in house prices in geographically distant markets cuts prices by 2.1%.

9.2.3 Resales of Distressed Builder Sales

If shocked builders sell to different socio-economic groups than non-shocked builders, then there should be a difference in the quality of the homes these builders sell. In Table X I test this possibility by controlling for a host of home quality characteristics, such as roof type and foundation type, and find the results remain unchanged. Another way to test if shocked builder homes have lower quality involves analyzing resales of builder homes. The builder’s original financial condition should not affect the price of the home in the future. Therefore, if a distressed builder home’s price is discounted due to the financial condition of the builder, and not due to fundamentals of the home or its clientele, then the price of the home will converge with time to the prices of non-distressed builder homes.

To investigate this idea, I test if the financial condition of the home’s builder, as captured by the builder’s exposure to crisis areas, $\overline{\Delta HP}_{j,06-09}$, predicts the home’s annualized rate of return. Equation 9 reports this relationship. I regress the annualized return R of house i , first sold by builder j in quarter t_1 of 2009, and sold for a third time in quarter t_3 , in county k , on builder j ’s shock measure $\sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09}$, which I denote as $\overline{\Delta HP}_{j,06-09}$. Here I include fixed effects ρ_{i,t_1,t_3} for the quarter of the first sale interacted with the quarter of the third sale. If a distressed builder home is not of lower quality than other builder homes, then as the distressed builder home is sold in the future, its price should converge to other home prices, resulting in a greater annualized return R and therefore a negative β_1 .

$$R_{i,t_1,t_3,j,k,09} = \beta_1 \sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09} + \beta_2 HP_{t_1,k} + \beta_3 X_i + \gamma_{s(i)} + \rho_{i,t_1,t_3} + \varepsilon_{i,t_1,t_3,j,k} \quad (9)$$

Table XIII reports the results. β_1 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. The shock is calculated over 2006-2009, as in Equation 2. The coefficients are statistically significant at the 10% level, although this is a standard I do not apply in the rest of the paper. These results weakly suggest that home prices of distressed builders may converge to prices of other homes over time, potentially implying that quality may not have driven their initial discount. I restrict here to homes sold by builders in 2009 that have been resold twice within the 2009-2015 period, which leaves a very small sample of just 1,470 homes. More data on these homes' subsequent sales is needed to determine whether their prices converge to other home prices over time.³³

10 Conclusion

This paper uses granular data on home builder housing developments to present new evidence on firm internal capital markets and prices. I use the home building industry as a natural laboratory because it allows me to overcome key challenges related to studying internal capital markets: I identify firm projects using housing developments, and geographic separation of developments allows for clean identification. I show that during the last housing crisis, home builders who lost money in housing bust markets cut prices on homes they sold in unaffected markets in order to generate sales quickly. Builders exposed to a 10% (\sim one

³³In the results using only second sales of homes rather than third sales, the results are not significant, possibly due to persistence of the price discount over short time frames.

Table XIII
Robustness: Resales of Existing Homes

This table explores the effect of builders' exposure to other housing markets on the home's annualized return. The dependent variable is the annualized rate of return on the house between the quarter of the home's first sale, t_1 , and the quarter of the home's third sale, t_3 . The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code by year month fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	-0.870 (0.490)	-0.889 (0.531)	-0.894 (0.539)	-0.895 (0.538)
Year x Zip	Yes	Yes	Yes	Yes
County HP	No	No	No	No
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
3rd Sale Pair FE	Yes	Yes	Yes	Yes
R^2	0.151	0.151	0.151	0.151
N	1470	1470	1470	1470

standard deviation) decline in the value of projects in other markets cut prices in unaffected markets by 2.2%. Consistent with models of internal capital markets, the tendency to cut prices in unaffected projects following a loss in another, distant project is stronger for more financially constrained firms. I find results only during the housing bust and not during the boom because financial constraints were not binding in the boom period. Consistent with financially constrained builders only cutting prices in order to generate cash flow quickly, I

show that when builders cut prices they sell homes faster and that builders are more likely to spread price shocks to areas where price cuts lead to larger declines in time-to-sale.

This paper contributes to a large literature on the effects of financial frictions on economic activity. When financial frictions force firms to rely on internal funds, shocks to one project in a firm can affect unrelated projects. These spillovers matter because they imply that financing constraints prevent firms from setting prices optimally. Moreover, they indicate that negative economic shocks spread across geography via firm internal capital markets.

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11 Appendix

11.1 Validate New Home Sales and Builder Assignment

I validate my measure of new home sales in this section by comparing new Census housing permits to new home sales in my main estimation sample. First, I pull new housing permits

for only those counties which appear in Corelogic. The Census reports housing permits according to category of home, in particular, 1, 2, 3, and 4+ unit dwellings. I focus on single family, condominium, and duplex homes in Corelogic, so to match this definition as closely as possible in the Census, I restrict to 1-3 unit dwellings.³⁴ Reassuringly, the correlation between my measure of new homes and Census new housing permits is 0.93. Figure 10 plots the behavior of the two measures over time at the month level. Note that the two measures should not be exactly the same because the Census reports housing starts, whereas Corelogic reports finished home sales. As a result, we should expect a slight lag between the two. Additionally, since there will be some housing constructions that are started but never completed, the Census number of new housing starts may exceed the Corelogic number of new homes sold. Overall, the two measures track each other closely, indicating my identification of new homes is accurately picking up new house sales.

Next, I pull industry data to validate my classification of homes to builders. Recall that I apply string matching methods to builder names from Corelogic transactions, and group together homes according to these resulting company names. If my methods were not adequate, then I should end up with market shares for builders that do not align with shares reported in trade publications. To test this, I pull yearly rankings of builders from “Builder Magazine,” an online trade report, in which rank is determined by number of homes sold. I then rank builders in Corelogic in each year based on their number of homes sold. I plot these two sets of rankings against each other in Figure 11. The plot comes close to fitting a 45 degree line, indicating that if a builder is ranked as number one in the trade publication for selling the most homes that year, then I will also rank this builder as number one in Corelogic for selling the most homes in that year. Over the full sample, approximately 60% of firms listed in the trade publication appear in Corelogic.

³⁴The 4+ unit dwelling Census category includes large condominiums which do not appear in my Corelogic sample.

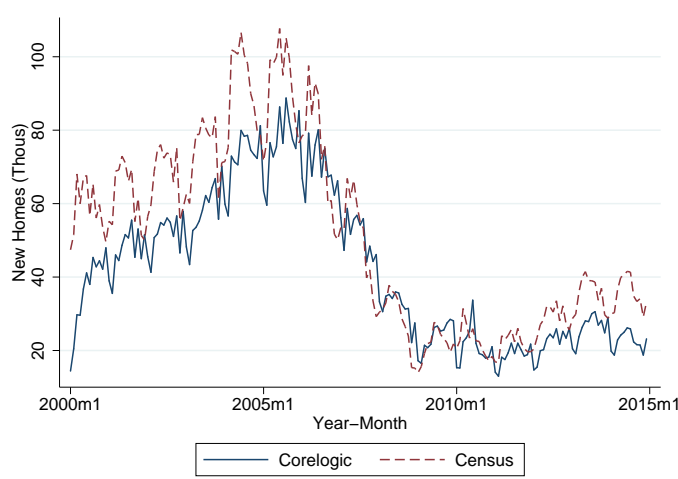


Figure 10. Comparison of Corelogic new homes sold against Census housing permits. This figure validates my identification of new home sales by comparing my measure to the number of new housing permits reported by the Census at the month level. I classify new home sales from Corelogic as the first sale made of a newly built home. From the Census, I pull housing permits only for those counties which Corelogic also reports. The Census reports housing permits according to category of home, in particular, 1, 2, 3, and 4+ unit dwellings. I focus on single family, condominium and duplex homes in Corelogic, so to match this definition as closely as possible in the Census, I restrict to 1-3 unit dwellings. The correlation between my measure of new homes and Census new housing permits is 0.93.

11.2 Survival Analysis

In Section 6.2 I show that time-to-sale is associated with a builder's exposure to other markets using OLS. However, OLS assumes the outcome variable, which here is time-to-sale, is normally distributed. Duration data are frequently skewed to the right meaning OLS assumptions may not hold. I investigate this concern in this section. I model the duration from listing to home sale as a function of a builder's shock measure assuming listing times have a Weibull distribution. A Weibull distribution permits right skewness. I compare survival functions for homes sold by builders with above median shock values to homes sold by builders with below median shock values in Figure 12. The survival function is the percentage of a builder's homes unsold by time t . Survival rates for builders with more negative shocks, (i.e., with "below median shocks"), are significantly lower than rates for builders with more positive shocks. This indicates that in any time t , homes on the market

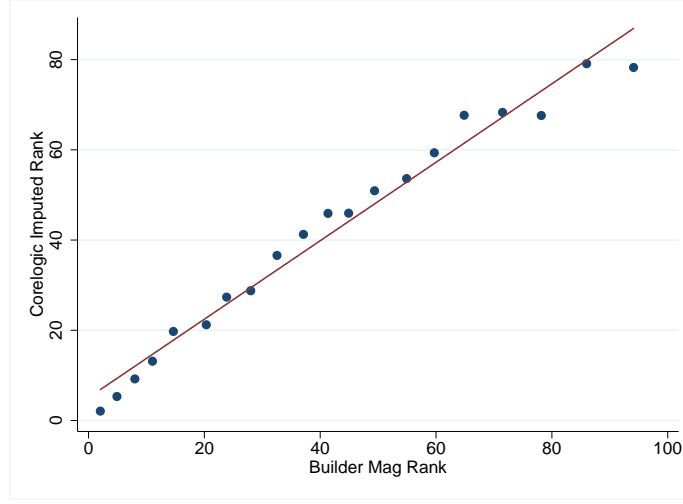


Figure 11. Comparison of external home builder market share to Corelogic home builder market share. This figure validates my classification of homes to builders. It compares builder market shares calculated from Corelogic to builder market shares reported in an online trade publication. I pull yearly rankings of builders from a trade report in which rank is determined by number of homes sold. I then rank builders in Corelogic in each year based on the reported number of homes sold. I plot these two sets of rankings against each other. Over the full sample, approximately 60% of builders listed in the trade publication appear in Corelogic.

owned by builders with more negative shocks are more likely to sell in time t , than homes owned by builders with more positive shocks.

11.3 Probability of Sale in Year after Construction

Section 6.2 shows that amongst the sample of builder homes that match to listings data, constrained builders sell homes faster. In this section, I validate this finding using year built and sales data for the full sample of builder homes. To do this, I create an indicator variable equal to one if the builder sells a home in a year following its year of construction. I then test if a builder's exposure to housing bust markets is associated with a lower probability of selling homes in a year after they are built. Table XIV reports results from Equation 2 in which the outcome variable is now a dummy for selling a home in a year following its construction. The sample now includes sales of homes occurring during the crisis years, 2009

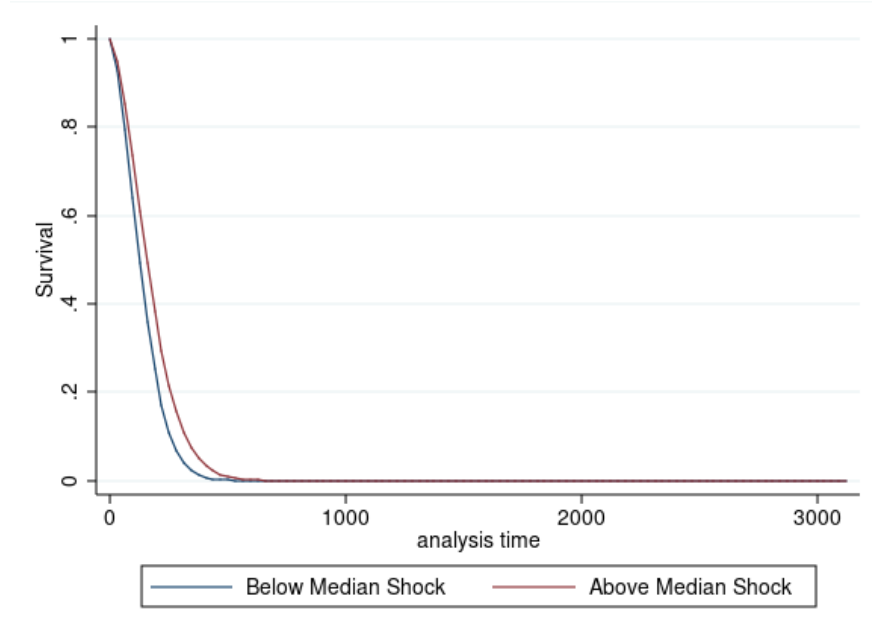


Figure 12. Survival rates for unsold homes. This figure plots the percentage of unsold homes a builder can expect to have remaining at time t , for builders with above and below median shock values, where shock refers to exposure to other housing markets.

to 2012, so as to exploit variation in sale year. β_1 from Equation 2 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. Interpreting the coefficient from column 4, I find that builders exposed to a negative 10% shock, (roughly one standard deviation of the shock), are 2.4% less likely to sell a home in a year after it is built.

11.4 Time-to-sale Sensitivity Sample Construction

I use the full MLS listings data to analyze how time-to-sale responds to price changes. I clean the dataset by first keeping only listings that result in a closed sale transaction. I also drop duplicate listings and any listings where the listing occurs after the close date. I use the original list date and close date to construct a measure of a home's time on the market. I drop counties with few sales transactions, where the total number of sales is less than 1,000.

Table XIV
**Probability of Sale in a Year after
Construction and Builders' Exposure to
Other Markets**

This table explores the effect of builders' exposure to other housing markets on the probability a builder sells homes in years after the homes are built. The dependent variable is an indicator equal to one if the home sells in a year after it is built. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). The sample consists of first sales of new homes occurring in 2009. All regressions are ordinary least squares (OLS) and include zip code by year fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	0.252*** (0.0555)	0.244*** (0.0557)	0.242*** (0.0558)	0.244*** (0.0560)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.207	0.207	0.207	0.210
N	310275	310275	310275	310275

I further drop counties with a short history in the sample, where the first recorded listing in MLS does not occur until 2002. I then restrict to listings occurring between 2007 and 2008, to correspond to the builder's information set in 2009. I restrict to counties that sell at least 20 homes in 2009 and drop observations in the top and bottom 5% of county time-to-sale sensitivities to price.

11.5 Correlation of Errors within Builders

A possible concern with Equation 2 is that homes sold by the same builder in a county will have the same shock, and therefore highly correlated errors. To allow for this structure in the errors, I also cluster the standard errors at the builder level. The results are reported in Table XV. The standard errors are only marginally larger than those from clustering at the county level, and the effect remains highly significant.

Table XV
Robustness: Cluster by Builder

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by builder and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\Delta HP_{j,06-09}$	0.401*** (0.0918)	0.226*** (0.0464)	0.226*** (0.0462)	0.218*** (0.0448)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.630	0.813	0.813	0.817
N	97522	97522	97522	97522

11.6 Non Overlapping Shock

In Equation 2 the outcome variable, house prices in 2009, overlaps with the final year of the shock measure, which is calculated over 2006 to 2009. This overlap makes reverse causality a concern. To address this possibility, I re-estimate Equation 2 using house prices in 2010 as the outcome variable. Table XVI reports the results. β_1 is reported in the first row along with its standard errors. Each column of the table corresponds to a specification with a different set of housing characteristic controls. The shock is calculated over 2006-2009, as in Equation 2. Across every specification, the effect is slightly stronger in the nonoverlapping specification than the overlapping one, and statistically significant, indicating that reverse causality is not driving the results.

11.7 Specification in Differences

My main results rely on a specification in levels. However, if the outcome variable, house prices, is autocorrelated, then the results will be biased. I address this possibility by testing a specification in first differences. It is not possible to take differences between two first sale prices of a home: a home can only be sold by a builder to a home-buyer once. I instead take differences over a builder's average sale price in a county between 2006 and 2009.

In particular, I estimate Equation 10 below:

$$\Delta(\text{SalePrice}_{j,k})_{06-09} = \alpha + \beta_1 \Delta(\text{samecounty})HP_{k,06-09} + \beta_2 \sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09} + \varepsilon_{j,k} \quad (10)$$

I regress the change in builder j 's average sale price in county k , between 2006 and 2009, on builder j 's shock measure, which is calculated as before, in Equation 2. The weights used in the shock measure are defined as in Equation 1, as the fraction of the number of homes builder j has sold in 2006 in county r , over the total number of homes builder j sold in 2006.

Table XVI
**Robustness: Non-Overlapping
Specification**

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the housing transaction level. The dependent variable is the log of house prices in 2010. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and log county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	0.423*** (0.0867)	0.237*** (0.0390)	0.237*** (0.0391)	0.231*** (0.0380)
Zip FE	Yes	Yes	Yes	Yes
County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.680	0.831	0.831	0.834
N	78425	78425	78425	78425

A house price shock between 2006 and 2009 in county r matters relatively more for a builder who derives a higher percentage of her 2006 homes sold from county r . I include controls $\Delta(\text{samecounty})HP_{k,06-09}$ for the average change in own county house prices between 2006 and 2009. This specification aggregates away house specific information. Standard errors are clustered at the county level throughout.

Column 1 of Table XVII reports coefficients β_1 and β_2 from this specification, where I denote the weighted percentage change in house prices $\sum_{r \neq k}^K \omega_{06,r,j} \Delta(HP_r)_{06-09}$ as $\overline{\Delta HP}_{j,06-09}$,

as before. The positive sign and statistical significance of the coefficient on $\overline{\Delta HP}_{j,06-09}$ indicates that builders spread price shocks to unaffected counties. Reassuringly, these results indicate that the effect found in Table IV is not driven by autocorrelation in house prices.

I next test for an effect during the boom using the same specification. Column 2 of Table XVII reports coefficients β_1 and β_2 from Equation 10 that has now been shifted back to the boom period, 2002 to 2005. The coefficient on $\overline{\Delta HP}_{j,02-05}$ is statistically insignificant and much smaller in magnitude than the effect during the crisis. Thus, using specifications in levels and in differences, I find that builders spread shocks only during the crisis and not during the boom.

11.8 Additional Robustness

Table XVII
Robustness: Specification in Differences

This table explores the effect of builders' exposure to other housing markets on their pricing, measured at the builder county level. The dependent variable in Column 1 is the difference in a builder's average sale price in a county k between 2006 and 2009. The dependent variable in Column 2 is the difference in a builder's average sale price in a county k between 2002 and 2005. The independent variable in Column 1 is the builder's exposure to house price changes in distant counties in 2009. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has homes in. The change in house prices in a county is calculated using Zillow. The weights are the ratio of the number of homes builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). The regression in column 1 includes the control $\Delta(\text{samecounty})HP_{k,06-09}$, the average change in own county house prices between 2006 and 2009. The independent variables in Column 2 are the same as in Column 1 but calculated over the period 2002-2005. All regressions are ordinary least squares (OLS). Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms	
	(1)	(2)
$\overline{\Delta HP}_{j,06-09}$	0.208** (0.0794)	
$\Delta(HP_k)_{06-09}(\text{samecounty})$	0.456*** (0.0859)	
$\overline{\Delta HP}_{j,02-05}$		-0.0753 (0.0706)
$\Delta(HP_k)_{02-05}(\text{samecounty})$		0.746*** (0.0864)
R^2	0.0246	0.0519
N	5316	4450

Table XVIII
Robustness: Control for Δ of
 $\log(HousePrices_k)$

This table explores the effect of builders' exposure to other housing markets on their pricing, using the log change in county house prices as a control. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant counties. A builder's exposure, in a particular county k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other counties the builder has sold homes in. The change in county house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given county, over the total number of homes the builder sold in 2006 (excluding sales in county k). All regressions are ordinary least squares (OLS) and include zip code fixed effects and the change in county house prices. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\Delta HP_{j,06-09}$	0.399*** (0.0841)	0.225*** (0.0373)	0.225*** (0.0373)	0.217*** (0.0376)
Zip FE	Yes	Yes	Yes	Yes
Δ County HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.630	0.813	0.813	0.816
N	97522	97522	97522	97522

Table XIX
Robustness: Exposure at Zip Code Level

This table explores the effect of builders' exposure to other housing markets on their pricing, calculated at the zip code level. The dependent variable is the log of house prices in 2009. The independent variable is the builder's exposure to house price changes in distant zip codes. A builder's exposure, in a particular zip code k , is defined as the weighted average of the change in house prices between 2006 and 2009 in all other zip codes the builder has sold homes in. The change in zip code house prices is calculated using Zillow. The weights are the ratio of the number of homes the builder has sold in 2006 in a given zip code, over the total number of homes the builder sold in 2006 (excluding sales in zip code k). All regressions are ordinary least squares (OLS) and include zip code fixed effects. Standard errors are clustered by county and are reported in parentheses. ***, ** and * denote statistical significance at the .1%, 1% and 5% levels, respectively.

	All Firms			
	(1)	(2)	(3)	(4)
$\overline{\Delta HP}_{j,06-09}$	0.405*** (0.0758)	0.222*** (0.0375)	0.222*** (0.0375)	0.220*** (0.0388)
Zip FE	Yes	Yes	Yes	Yes
Zip HP	Yes	Yes	Yes	Yes
Sq. Ft.	No	Yes	Yes	Yes
Baths	No	No	Yes	Yes
Prop. Type FE	No	No	No	Yes
R^2	0.622	0.802	0.802	0.804
N	81345	81345	81345	81345