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Do Parents Matter? Effects of Lender Affiliation Through the Mortgage Boom and Bust

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It is widely acknowledged that the 2007 mortgage crisis was preceded by a broad deterioration in underwriting diligence. This paper shows that this deterioration varied by the industry affiliation of mortgage lenders. Loans issued by homebuilders and stand-alone lenders were significantly less likely to default than loans issued by depository banks and affiliates of major financial institutions. I argue that homebuilders and stand-alone lenders had the least financial capacity to hold mortgages, and their resulting need to sell loans quickly on the secondary market forced them to issue safer loans. Tests of other explanations, including differences in information and incentives to avoid foreclosure externalities, receive little support. This study highlights a novel means by which firm boundaries influence firm adaptation to changing market conditions by defining the boundaries of the internal capital markets and hence the relative constraints of constituent units.

1. Introduction

One of the precursors to the housing crisis that began in 2007 was a sharp decrease in mortgage underwriting quality earlier in the 2000s (Demyanyk and Van Hemert 2011, Dell'Ariccia et al. 2012). Despite substantial research on the underlying factors that led to this lending deterioration (e.g., Mian and Sufi 2009, Keys et al. 2010, Rajan et al. 2014), the role of mortgage lenders has received relatively little attention. Aside from exploring the effects of vertical disintegration and the corresponding decline of "skin in the game" (Purnanandam 2011, Demiroglu and James 2012), studies generally assume lenders are relatively homogeneous. This, however, is far from the case. All major depository banks had lending units during the period in question, as did major investment banks, many insurance companies, and national homebuilders. The heterogeneity of parent industries raises the question: How did these units' corporate affiliations affect lending quality during this period? The answer to this question is relevant not only for isolating underlying causes for the housing downturn but also for addressing a long-standing question in corporate strategy: How do firm boundaries influence how firms adapt to changing external conditions?

This latter question has led to a large and active research agenda. Recent studies have typically adopted a transactions cost (Williamson 1975, 1985) or capability development (Wernerfelt 1984, Barney 1986) approach to the question. A small sample of these studies reveals that firm boundaries influence complex problem solving (Macher 2006), coordination in

uncertain and changing environments (Forbes and Lederman 2009), and capability development in general (Jacobides and Winter 2005). Other studies emphasize the darker side of integration as leading to coordination costs (Rawley 2010, Rawley and Simcoe 2010, Zhou 2011) and agency or social conflicts (Nickerson and Zenger 2008, Pierce 2012). This study, in contrast, suggests a less explored means by which firm boundaries affect adaptation—through their impact on the relative financial resources and constraints of constituent units.

In the popular view, there is a widespread presumption that lending quality did, in fact, vary by type of parent affiliation. Homebuilders, which sold nearly 30% of new homes in the United States during the 2000s and financed up to 70%–80% of these homes,[1] have been subject to several consumer and shareholder lawsuits, as well as government investigations accusing them of engaging in particularly poor lending practices to sell more homes.[2] Furthermore, during

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[1] Homebuilders comprised an even larger market share in boom geographies, financing 51% of all new homes in Phoenix and 47% in Las Vegas. Whereas mortgages for new homes comprise less than 10% of the total residential mortgage market in the United States, the residential construction industry accounts for approximately 4%–5% of the U.S. gross domestic product (Bipartisan Policy Center (http://bipartisanpolicy.org, accessed June 10, 2010), "Bonfire of the Homebuilders" (*Businessweek*, August 13, 2007), and the author's estimates from 10-K filings and data used in this study).

[2] Some cases include *In re*: *Beazer Homes USA, Inc. Securities Litigation* (No. 1:07-CV-725-CC (N.D. Ga.)), *Mark Zachary v. Countrywide Home Loans Inc. and Countrywide KB Home Loans* (No. 4:08-CV-00214 (S.D. Tex.)), and *Sodalin Kaing v. Pulte Homes, Inc., et al.* (No. C09-05057 (N.D. Cal.)); see also HUD Audit Reports 2009-LA-1018,

Figure 1(a) **Market Share of New Home Purchase Mortgages by Each Lender Type by Year**
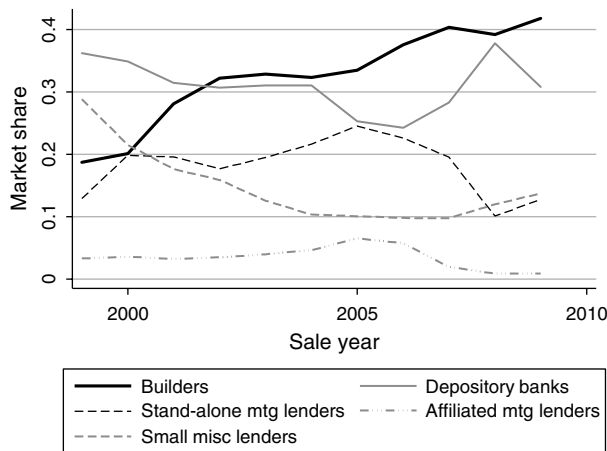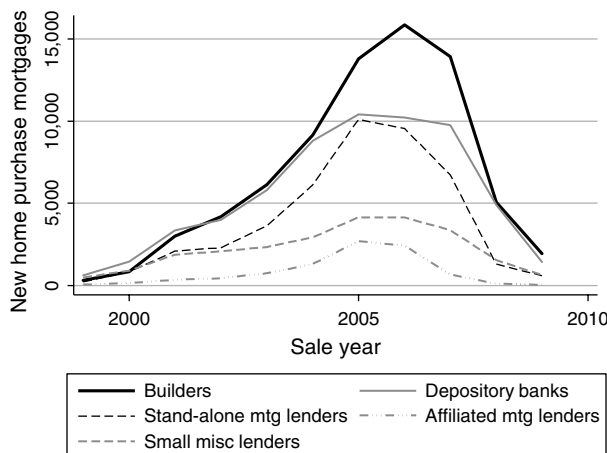

Figure 1(b) **Number of New Home Purchase Mortgages Underwritten by Each Lender Type by Year**

this period of unprecedented home sales and price appreciation, homebuilders' share of new home mortgages grew relative to other lenders' (see Figure 1(a)). This increased share suggests that homebuilders were "buying deep" into the risk pool to sustain sales growth, particularly as sales began to level off in late 2005 and 2006 (see Figure 1(b)). In fact, in the aftermath of the collapse, homebuilder mortgages defaulted at roughly 130%–150% of the national average, according to CoreLogic. This poor performance appears to confirm popular accounts and support prior models of captive finance that explain lower lending quality by in-house lenders as efficient cross-subsidization of the durable good (Barron et al. 2008).

This study disputes this interpretation. It finds that the higher default rate of homebuilder loans is entirely

attributable to the concentration of new construction in particularly risky geographies, and in fact, controlling for geographic factors, homebuilders applied significantly more diligence than other lenders. Using a data set of 212,058 mortgages issued by all market participants in the 100 zip codes that experienced the most new home construction from January 1999 to mid-2009, I evaluate lending quality as the hazard of loan default after controlling for macroeconomic, borrower risk, and contract characteristics. I compare the default hazard across four classes of lenders: homebuilders, stand-alone lenders, depository banks, and lenders affiliated with large financial institutions. Rather than underperforming the market, homebuilder loans perform significantly better than similar loans issued by depository banks and affiliates of large financial institutions. Interestingly, these quality differences emerge only with the peaks of the housing boom in 2005 and 2006. The relative hazard of mortgage default for loans issued by depository banks increased from being statistically indistinguishable from that of homebuilders' loans between 1999 to 2004 to being 36% higher in 2005 and 2006.

I explore three potential explanations for this finding. First, I ask whether financial constraints explain lending quality differences. In this scenario, firms with more constrained capacity to hold loans, including homebuilders and most stand-alone mortgage banks, underwrote mortgages that could be sold quickly and with a lower chance of forced repurchases as a result of poor underwriting quality.[3] The second explanation focuses on information differences between lenders. Here, homebuilders produce more soft information about customers and local market conditions as a by-product of their home sales and land operations. They use this information to screen customers more thoroughly and to respond better to imminent downturns in their local markets. The third explanation asks whether homebuilders' internalization of the costs of foreclosures in their subdivisions—costs that other lenders do not bear—drives higher lending standards.

Overall, I find support for the first explanation and no strong evidence for the second or third. Specifically, the hazard of loan default, conditional on a loan's observable characteristics, is positively related to the average loan holding period for a firm and to a supplementary pricing-related proxy for mortgage holding capacity. This proxy is defined as the degree to which the hard information on a loan explains loan prices. The logic behind this measure follows Rajan et al. (2014), who show that as securitization levels increased, loan pricing was increasingly explained by

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2006-LA-1014, 2006-LA-1001, as well as U.S. Securities and Exchange Commission (SEC) and Department of Justice investigations into Beazer Homes USA.

[3] Forced repurchases arise from early default, violation of stated underwriting guidelines, or fraud—all of which increase with poor underwriting.

hard information. Taken together, I interpret these results as evidence that markets did, in fact, exert a disciplining force at the height of the boom, particularly for lenders with limited loan holding capacity.[4]

These findings suggest an interesting and previously unexplored relationship between internal capital markets and firm adaptation. One defining feature of internal capital markets is that managers engage in "winner-picking," allocating capital to units at levels above what would be available via the external market (Williamson 1975, Donaldson 1984). Stein (1997) also demonstrates that, to provide capital to winners, managers must engage in "loser-sticking": undersupplying capital to other units, even if those units have profitable investment opportunities. A given unit, therefore, may be resource constrained within one firm and resource rich in another, solely as a function of the other opportunities within the firm boundaries. These constraints, in turn, influence how the firm adapts to changing conditions.

In the housing context, the findings are consistent with homebuilders' mortgage units being "loser-stuck," particularly as the housing boom progressed and headquarters allocated an increasing share of capital to housing operations. The findings further suggest that these loser-stuck units and other constrained lenders responded to market growth with relatively more discipline than unconstrained lenders.

For integrated homebuilders, this result is counterintuitive, as prior research on captive lending and lender segmentation predicts that the mortgage units might optimally lower their screening levels to subsidize housing units (Barron et al. 2008) or as they specialize (Remolona and Wulfekuhler 1992, Carey et al. 1998). The results of this paper show the opposite: that homebuilders both served observably less risky segments and had higher underwriting diligence. This result also runs counter to prior research that has shown that integrated firms are generally less disciplined than markets (Williamson 1985).

This research is closely related to two recent papers. Seru (2014) shows that conglomerates reduce research and development (R&D) productivity in acquired firms, particularly in acquirers with active capital markets.[5] Lyandres (2006) suggests that conglomerates affect rival competition in product markets by requiring divisions to share a unified firmwide capital structure. Although the specific mechanisms differ, both these papers and the current study note that end-market activity is influenced by internal capital allocation that is in turn determined by firm boundary choice.

This paper also makes two contributions to the large and growing literature on the causes and consequences of the recent housing crisis (e.g., Foote et al. 2008, Shiller 2008, Mayer et al. 2009). First, it provides evidence that contradicts the perspective that the "originate-to-distribute" lending model, on its own, led to poor underwriting practices during this period (Purnanandam 2011, Demiroglu and James 2012). A high-securitization environment may, indeed, have contributed to poor systemic underwriting (Keys et al. 2010, Rajan et al. 2014) and exacerbated the foreclosure crisis (Piskorski et al. 2010). Within this environment, however, I find that firms with limited capacity to hold loans before selling them to third parties were more disciplined than firms with more funding options. Second, this paper shows that the systemic deterioration in lending quality over the course of the boom (Dell'Ariccia et al. 2009) was not evenly shared by originators. In fact, some of the firms that displayed the greatest deterioration—depository banks—were also the most regulated, a finding similar to that of Keys et al. (2009).

Finally, this paper contributes to research on credit markets. Prior credit research outside of the housing context has shown that specialized lenders, which include captive industrial lenders analogous to the homebuilders in this paper, serve observably riskier customer segments independent of geography (Carey et al. 1998, Barron et al. 2008) and show evidence of agency issues (Pierce 2012). None of these findings was validated in this context; in fact, they were contradicted.

2. Mortgage Industry in the 2000s
The first half of the 2000s was marked by 100% home price appreciation between 2000 and 2006[6] and increased housing construction from 1.5 million new

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[4] These findings are consistent with statements from industry participants interviewed for this study. For example, a former head of the mortgage affiliate of one of the largest national homebuilders stated during an interview, "There is a stereotype that securitization led to this hot potato, that's where the risk was. In reality . . . the opposite was true. It was the portfolio lenders, including the securitization issuers, who went out like riverboat gamblers. If I am a bank, I can put $8 billion into a new product tomorrow. If I rely on the market [to fund mortgages], there's only so quickly it can adapt to new products. The market was a well-oiled machine and relied on known products. Anything new was done in-house . . . . [W]e never originated a mortgage without knowing where we would place it." The former head of the lending affiliate of another large national homebuilder made a similar remark when asked what drove strict underwriting standards: "We made 15%–40% margin on our homes; why tie up capital in mortgages? We had a $100 million line, [and] we had to turn it over every 30 days to free up capital to make new loans."

[5] In the management literature, Baysinger and Hoskisson (1989) and Hoskisson et al. (1993) note a similar empirical finding, although they attribute the costs to inefficient monitoring and incentives associated with diversification, rather than internal capital markets.

[6] S&P Dow Jones Indices. S&P/Case-Shiller 20-City Composite Home Price Index (http://us.spindices.com/indices/real-estate/sp-case-shiller-20-city-composite-home-price-index, last accessed July 18, 2014).

homes per month in mid-2000 to 2.3 million in early 2006.[7] Concurrent with these trends was an increase in securitization, combined with an increasing reliance on pricing loans based on "hard information," particularly a consumer's FICO (credit) score (Rajan et al. 2014).[8]

Beginning in 2005 and 2006, national home prices and sales both leveled off. In the first half of 2007, the private-label (non-government-backed) securities market effectively shut down, leading to the failure of numerous mortgage lenders.[9] By January 2010, national home prices had fallen 30% from their peak, including 55%, 50%, and 46% in Las Vegas, Phoenix, and Miami, respectively.[10] By March 2010, 24% of all U.S. residential properties with mortgages were worth less than the mortgages on the properties, including 70% of all properties in Nevada, 51% in Arizona, and 48% in Florida.[11] This housing crash triggered a financial crisis that precipitated the largest recession since the Great Depression.

2.1. Mortgage Origination

The mortgage industry spans both the primary market to supply loans to consumers and the secondary securitization market in which originators transfer the loans via bulk sales to third parties (or to a different division within the same firm) and pool them into trusts that issue mortgage-backed securities. For bulk sales, lenders periodically assemble a pool of loans and either offer the pool to a specific purchaser or place it for bid. Purchasers have two levers to ensure loan quality. First, they can "kick out" loans from the pool that they deem to be poor quality.[12] Lenders can then attempt to reoffer kicked-out loans to other buyers; however, these loans often take longer to place and are sold at a discount. Second, they can "put back" loans by forcing lenders to repurchase the loans postsale if any representations and warranties in the loan purchase agreements are violated. Similar to kicked-out loans, these repurchased loans typically can be resold but only after a period of time and often at a loss rate of

approximately 25%, according to practitioners interviewed for this study. Although no industry-wide data are available, practitioners report that purchaser due diligence began increasing in early 2005 as home price appreciation began to slow down and then dramatically increased in 2006 and 2007 as home prices leveled and defaults rose.[13]

I categorize mortgage lenders into four parent industries used in later analyses: stand-alone mortgage lenders (such as Countrywide), depository banks (including both commercial banks such as Bank of America and thrifts such as Washington Mutual), mortgage lenders affiliated with larger firms (including the lending arms of AIG, GE Capital, and Lehman Brothers), and homebuilders with financing affiliates.

2.2. Homebuilders' In-House Mortgage Units

Homebuilders established mortgage units beginning in the 1960s and continuing through the 1990s. By 1999, nearly all the national and large regional homebuilders had established internal divisions with specialized loan officers and underwriters, whereas midsized homebuilders typically had joint ventures with financial institutions. These in-house units generally funded only mortgages associated with homes constructed by the parent homebuilder. In interviews, homebuilder executives report that the rationale for establishing in-house units was the desire to reduce customer dropouts during the home closing process by improved coordination between financing and home sales activities.

During this period, homebuilders and most stand-alone mortgage lenders disposed of their loans on the secondary market through sales to large financial institutions. Prior to these sales, mortgages were funded by revolving credit lines with financial institutions. These credit lines were typically small relative to home sales. For example, Pulte Homes, the largest U.S. homebuilder, reported a $955 million credit line in 2006. With annual home sales of $14 billion, this credit line allowed for mortgages to be held for 16 to 30 days prior to sale.[14] A kick-out rate of 14.95%, the level reached by the New Century Financial Corporation in December 2006, would consume 25%–40% of the line.[15]

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[7] U.S. Census Bureau. New privately owned housing units started— seasonally adjusted annual rate. Last accessed July 18, 2014, https://www.census.gov/construction/nrc/pdf/startssa.pdf.

[8] The name FICO was derived from the former name of the firm that created and manages the consumer credit scoring model, the Fair Isaac Corporation.

[9] The Mortgage Lender Implode-o-Meter lists 384 lender failures since late 2006, http://ml-implode.com/, accessed June 14, 2010.

[10] S&P/Case-Shiller via http://www.calculatedriskblog.com, accessed May 21, 2010.

[11] CoreLogic Equity Report, first quarter 2010.

[12] For example, New Century Financial Corporation experienced a 14.95% kick-out rate by December 2006 prior to bankruptcy in early 2007 (New Century Financial Corporation Examiner's Report, Case No. 07-10416, p. 161).

[13] The bankruptcy examiner for New Century Financial Corporation reported that in 2005, 20%–30% of the loan files in New Century pools would be fully examined by investors. By 2006, 30%–35% of loan files had been examined, and by late 2006, some investors had examined every loan file (New Century Financial Corporation Examiner's Report, Case No. 07-10416, p. 163).

[14] The calculation uses data reported in Pulte's 2006 10-K filing: ($955 million credit facility × 85% utilization)/($14 billion × 90% capture rate × 80% loan-to-value) = 29 days. Pulte reported an average of 47% utilization—common in the industry, to allow for seasonal fluctuations—which allowed mortgages to be held for 16 days before sale.

[15] Assuming a 60- to 90-day placement rate.

3. Underwriting Differences by Lender Affiliation

3.1. Data and Sample Selection

The primary data sources are county deed records and the Loan Performance Servicer database, which were merged for this study in cooperation with CoreLogic, the data provider. The county deeds database consists of the complete public deed filings, including all liens related to purchases, refinancing mortgages, and notices of default and foreclosure. The Loan Performance Servicer database consists of mortgage servicer-provided information that covers approximately 80% of all mortgages in the United States and includes borrower risk information and important contract provisions.[16] I supplement these two sources with data on the lender that was hand-collected or merged from Compustat (for public firms) and macroeconomic data from the Census Bureau, the Bureau of Labor Statistics, Freddie Mac, and the Federal Reserve Bank.

3.1.1. Variables.

The outcome variable is an indicator of whether a notice of mortgage default was filed with the county, together with the date of filing.[17] Variables that control for macroeconomic conditions and mortgage features are listed in the appendix. Lender industry categories and characteristics were hand-collected, merged from Compustat, or generated from the mortgage data. Because of the long tail of mortgage lenders in the database, industry categories were assigned to a sufficient number of lenders to cover 80% of the loans in the database. The 270 hand-coded lenders were assigned to four categories: homebuilders (Standard Industrial Classification (SIC) codes 1520 and 1531), depository banks (SIC codes 6020, 6021, 6022, and 6035), stand-alone mortgage lenders (SIC codes 6162 and 6163), and affiliated mortgage lenders (SIC codes 4213, 6141, 6159, 6172, 6211, 6311, 6331, 6531, 6798, and 7200). The four categories include 34 homebuilders, 75 depository banks, 132 stand-alone mortgage lenders, 46 large affiliated mortgage lenders, and 3,287 small miscellaneous firms. Ten of the 34 homebuilders were joint ventures with banks. Although their homebuilder classification was retained, a joint-venture flag was added to all specifications. Joint-venture-funded loans comprise 15% of all homebuilder-financed loans in the sample. The remaining firms were allocated either to depository banks if their names included

certain search terms[18] or to the "small miscellaneous" category.[19]

3.1.2. Sample Selection and Descriptive Statistics.

The sample was constructed from all county deed filings for the top 100 zip codes for new home construction from 1999 to 2009. The zip codes are located mainly within California, Arizona, Nevada, Texas, and Florida, with the highest concentrations of construction in Las Vegas, Nevada and Phoenix, Arizona. Although not a nationally representative sample, the sample spans geographies that experienced substantial downturns (e.g., Nevada, Arizona, Florida) as well as those that were more stable (e.g., Texas and North and South Carolina). In aggregate, the combined home price index tracks the national home-price index closely.[20] Relative to a national sample, this data set includes a higher proportion of new home construction and, within new homes, a higher proportion of homes sold by national homebuilders. As such, the sample enables greater statistical power to compare loan quality between national homebuilders and financial lenders.[21]

The initial deed filings were screened for new-construction purchase mortgages, which provide an initial sample of 779,315 mortgages originated between January 1999 and September 2009. All mortgages designated as corporate owned, interfamily transfers, or private party sales, and all condominiums, townhouses, and other miscellaneous property types were then excluded. Mortgages with substantial missing or duplicate data (184,925 records) and Federal Housing Authority (FHA) and Veterans Administration (VA) mortgages (117,718 records) were also excluded.[22] After these exclusions, 476,672 purchase mortgages from the county filings were submitted to CoreLogic to be merged with the Loan Performance Servicer database.

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[16] The Loan Performance Servicer database should not be confused with the commonly used Loan Performance Securities database, which covers the subprime market only.

[17] Conditional on the mortgage not prepaying as a result of resale or refinance, which is treated as a nonfailure exit.

[18] The depository banks also include 401 small banks with a mean (median) of 26 (17) loans that had "Bank," "BK," "FSB," "CU," or "FCU" in their name, contributing less than 4% of depository bank loans. These banks do not materially affect the empirical results.

[19] The smallest 10 lenders that were coded each contributed an average of 38 loans, whereas the largest 10 lenders contributed an average of 26,170 loans; therefore, the incremental contribution of each additional lender was minimal.

[20] This sample experienced an 80% rise and 33% decline between 1999 and 2009, versus the national sample's 95% rise and 32% decline during the same period (see Footnote 6).

[21] Although not nationally representative, there is no reason to believe that lending quality patterns differ in this sample from the national average. Conservatively speaking, however, the result can be interpreted as quality patterns in particularly (and profitable) active markets.

[22] The FHA and VA are both government agencies. These mortgages were excluded for two reasons: first, FHA/VA mortgages are governed by separate regulations and, hence, behave differently from conventional mortgages. Most studies, unless specifically focusing on the FHA, exclude these mortgages. Thus, I also exclude them for comparability purposes.

Table 1   Descriptive Statistics

	Homebuilders $n = 74,262$	Stand-alone lenders $n = 44,550$	Depository banks $n = 60,657$	Affiliated lenders $n = 8,087$	Small misc. $n = 24,502$
Mortgage amounts and prices					
Sale amt ($)	281,602	288,060	296,932	280,088	277,779
Mtg amt ($)	213,353	220,912	226,681	215,453	213,428
Initial interest rate (%)	6.10	6.15	6.04	7.19	6.30
Borrower observable risk					
CLTV (%)	80.64	83.35	82.98	86.27	82.45
FICO	723	707.8	710.9	656.3	708
Low or no documentation (%)	56.62	67.99	36.01	49.65	51.85
Back-end DTI	18.66	25.24	15.66	15.14	15.97
Product type					
Adjustable rate mortgage (*ARM*) (%)	11.65	17.27	20.98	27.96	16.42
Fixed rate mortgage (*FRM*) (%)	76.53	63.66	67.19	32.56	75.09
Hybrid rate mortgage (%)	11.43	17.49	8.94	20.08	5.86
Balloon mortgage (%)	0.39	1.58	2.9	19.4	2.63
Contract terms					
Negative amortization (%)	5.44	14.76	7.77	1.6	9.22
Interest only (%)	21.96	27.35	17.65	34.95	16.1
Prepayment penalty (%)	5.45	22.04	13.59	50.89	17.65
Loan performance					
Notice of default (%)	7.86	13.65	7.89	21.76	9.2
Lender characteristics					
Log annual number loans	2,833	2,994	1,766	440	111
Lender independent (%)	0	98.63	59.03	3.98	100
Parent public (%)	92.01	38.7	96.54	86.84	0
Lender JV with bank (%)	14.96				

Note. See the appendix for variable definitions.

The match rate between the two databases was 44%, providing a final sample of 212,058 mortgages. Overall, an analysis of the merged sample reveals that the data are generally unbiased for this study, although the sample is not fully representative of the submitted data set. Table 1 shows the descriptive statistics on the merged database (refer to the appendix for variable definitions).

Overall, the descriptive statistics show that homebuilders generally targeted higher credit customers, issued mortgages with more conservative contract structures (higher proportion of fixed rate mortgages and lower proportion of negative amortization, interest-only, and prepayment penalty clauses), and had lower aggregate default rates.

3.2. Empirical Approach

I use a Cox hazard model to evaluate relative default risk between lender types. This model has several advantages. First, it accounts for home resales and mortgage refinancing that lead to nondefault-related exits from the data set. Second, it allows for the inclusion of macroeconomic controls that vary post-loan origination, such as local home prices and unemployment and national interest rates. Third, it makes more realistic assumptions regarding distribution of residuals than a linear model and accounts for right censoring of the data. Finally, it does not impose an underlying

functional form on the underlying mortgage default rate over time.[23]

I report all results as hazard ratios, equivalent to odds ratios in logistic models. Since these hazard ratios are exponentiated, they are nonnegative, centered on 1 (rather than 0), and have a multiplicative interpretation. As such, coefficients less than 1 represent a decrease in the relative hazard and coefficients greater than 1 represent an increase. The following model is used in the analysis:[24]

$$
\begin{aligned}
h(t \mid x_i) &= h_0(t) \exp\big(\alpha + \beta_0\, \text{ParentAffiliation}_i + \beta_1\, \text{Macro}_i \\
&\quad + \beta_2\, \text{Lender}_i + \beta_3\, \text{Risk} + \beta_4\, \text{Contract}_i + \beta_5\, \text{Price}_i \\
&\quad + \beta_{\text{year}}\, \text{YearFE}_i + \beta_{\text{st}}\, \text{StateFE}_i + \varepsilon_i \big),
\end{aligned} \tag{1}
$$

where $h(t \mid x_i)$ is the hazard of default of loan i at time t, conditional on the loan not being prepaid because of a sale or refinancing event; $h_0(t)$ is the baseline hazard. *ParentAffiliation* is a vector of five indicator variables for homebuilders, stand-alone mortgage lenders, depository banks, affiliated mortgage

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[23] I replicated the analysis using a logit specification and obtained qualitatively identical results.

[24] In unreported results, the findings are replicated using logit specifications.

lenders, and miscellaneous lenders (throughout the analysis, the homebuilders are the omitted lender type unless otherwise specified). *Macro* is a vector of macroeconomic controls that includes the home-price index constructed from repeat sales using the county deed records. *Lender* is a vector of lender controls; *Risk* is a vector of standard hard risk metrics on the borrower; and *Contract* is a vector of mortgage characteristics. *Price* includes the initial interest rate of the loan for all mortgages and the margin above an index if the loan is an adjustable-rate mortgage. *YearFE* and *StateFE* represent vintage (origination) year and state fixed effects, respectively. See the appendix for a more detailed definition of these variables.

The coefficients represented by β_0 are the main parameters of interest. If homebuilders issued relatively worse-performing loans than other lender types, then the β_0 estimates will be less than 1.

3.3. Results

Table 2 begins with a direct comparison of the default hazard of homebuilders and financial firms pooled across all years of the sample. Column (1) shows the unconditional relative hazard for the years 1999–2009. This specification allows for all choices by lenders to vary, including geography, macroeconomic conditions, and years in which to offer loans, as well as choice of borrower risk and contract characteristics. The results show that, allowing for geography and vintage year to vary, homebuilder loans have a lower default hazard than stand-alone and affiliated mortgage lenders and statistically the same as depository banks and miscellaneous firms. Columns (2) and (3) add in hard information controls, including lender and macroeconomic controls and fixed effects for vintage years and states in column (2) and observable risk and contract characteristics in column (3). In column (2), the hazard ratio coefficients on all the lender types are significantly greater than 1. For example, the hazard ratio for loans issued by depository banks is now 2.1385, more than twice as high the baseline of 1 for homebuilder loans, the omitted category. The difference between the results in columns (1) and (2) indicates that homebuilders offered mortgages in riskier geographies, years, and macroeconomic conditions than other lenders; however, controlling for those choices, the default hazard is lower. A comparison of the results in columns (2) and (3) shows that homebuilders targeted safer borrowers than the four financial lender types and that, conditional on that segmentation choice, the default hazard was lower than for financial lenders.

Column (4) includes interest rate as a proxy for "soft information." The logic here is that any borrower risk that is observed by the lenders, but not captured in metrics such as FICO and combined loan-to-value ratio, will be reflected in the interest rates that the

lender charges.[25] This model reflects the full specification in Equation (1). The coefficients on the parent affiliation indicators all attenuate compared to column (3), but they are still greater than 1 and significant. This indicates higher default hazard than for loans issued by homebuilders, even after controlling for loan characteristics.

Overall, Table 2 shows that homebuilders funded mortgages in riskier areas than other lenders. Within these areas, however, they targeted safer borrowers and offered safer mortgage contracts. In addition, after controlling for these choices, they also appeared to underwrite higher-quality loans. This underwriting could be due either to additional screening on soft information not fully reflected in mortgage prices or to a treatment effect in which homebuilders place borrowers into safer loans.

Table 3 reports relative default hazard across different time periods. I run the full specification as in column (4) in Table 2, subdivided by time period. For space reasons, only β_0, the coefficient on the parent affiliation indicators, is reported. The table shows the results over four main time periods during the housing cycle: the baseline years (1999–2002), the middle boom (2003–2004), the late boom (2005–2006), and the post boom (2007–2009).

The coefficients on parent affiliation indicators are insignificant during the 1999–2002 and 2003–2004 periods, indicating no statistical difference in lending standards by parent affiliation for loans issued during those years. During 2005 and 2006, the peak housing period, the coefficients on depository banks and affiliated lenders increase to 1.3582 and 1.5643, significant at the 1% level. Homebuilders' hazard remained lower than other lenders' during the post-boom period, 2007–2009, with the coefficient on stand-alone lenders at 1.5023 and depository banks at 1.4641. Overall, the results in Tables 2 and 3 provide evidence that lending quality did differ by parent affiliation and that these differences emerged only during the peak period of the housing boom, when lending standards were at their lowest level overall.

4. Explaining Lending Differences

I investigate three explanations for these differences. First, homebuilders have more constrained capacity to hold mortgages from origination until secondary market sale, and this constraint led to increased

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[25] Since interest rate is both a proxy for soft information and an outcome of other independent variables in the model, there is some question as to whether it should be included as a control. The results in the paper are qualitatively unchanged either way.

Table 2   **Hazard of Mortgage Default, 1999–2009**

	Hazard ratio (DV = *Notice of default*)			
	Unconditional (1)	Geo only (2)	Geo, risk, contract (3)	Geo, risk, contract, pricing (4)
Parent affiliation				
Stand-alone mortgage lenders	1.5672**	2.6829***	1.2519*	1.1984*
	(2.0680)	(4.1683)	(1.8884)	(1.7730)
Depository banks	0.9784	2.1385***	1.3586***	1.3317***
	(−0.1301)	(3.4760)	(2.8779)	(2.9521)
Affiliated mortgage lenders	2.5427***	3.9879***	1.6538***	1.5155***
	(5.0992)	(8.2475)	(5.6750)	(4.7852)
Misc lenders	1.0749	2.4814***	1.4077**	1.3587**
	(0.4656)	(3.7494)	(2.3117)	(2.1966)
Mortgage amount				
log(*Mtg amt*)			1.4738***	1.5338***
			(13.9356)	(16.7742)
Borrower observable risk				
CLTV			58.9151***	50.5540***
			(24.4874)	(24.4020)
FICO			0.9938***	0.9945***
			(−20.1116)	(−15.6915)
Low or no documentation			1.5355***	1.4651***
			(9.2688)	(9.1644)
Back-end DTI			1.0011	1.0017*
			(1.0933)	(1.7962)
Product type				
FRM			0.7209***	0.1209***
			(−5.7366)	(−7.9220)
Contract terms				
Negative amortization			1.2530**	1.9955***
			(2.4901)	(8.8159)
Interest only			1.2172***	1.1957***
			(4.1579)	(3.9078)
Prepayment penalty			1.1597**	1.0985**
			(2.4579)	(2.1272)
Pricing				
Initial interest rate				1.1209***
				(7.1847)
FRM × Initial interest rate				1.3241***
				(12.9751)
Margin				0.9925
				(−0.5814)
Macroeconomic characteristics				
Log tract 2000 med inc		0.6486***	0.6837***	0.6854***
		(−6.1155)	(−7.0098)	(−6.7972)
Freddie 30-yr rate		0.9466	1.0501	0.9110**
		(−1.4470)	(1.2427)	(−2.0974)
Fed funds rate		1.2437***	1.1861***	1.1570***
		(6.7046)	(5.3268)	(4.8952)
Regional home prices		0.1023***	0.1249***	0.1297***
		(−21.8502)	(−21.5806)	(−21.0024)
State-level unemployment		1.0514***	1.0688***	1.0716***
		(3.3881)	(4.7139)	(4.9474)
Lender characteristics				
Log annual number loans		1.0045	0.9772	0.9850
		(0.1074)	(−0.9328)	(−0.6531)
Lender independent		0.7822	0.9730	0.9708
		(−1.3412)	(−0.2613)	(−0.3395)

Table 2   (Continued)

	Hazard ratio (DV = *Notice of default*)			
	Unconditional (1)	Geo only (2)	Geo, risk, contract (3)	Geo, risk, contract, pricing (4)
Parent public		1.3847 (1.2598)	1.1063 (0.6897)	1.0123 (0.0849)
Parent log assets		0.9748 (−1.2825)	0.9895 (−0.8744)	0.9940 (−0.5097)
Lender JV with bank		1.3052 (1.2743)	0.8243*** (−3.0465)	0.8334*** (−2.8400)
YearFE	N	Y	Y	Y
StateFE	N	Y	Y	Y
Observations	211,551	211,551	211,551	211,551
Pseudo *R*-squared	0.003	0.067	0.090	0.092

Notes. This table compares the hazard of default of mortgages issued by lender type, with homebuilders the omitted category. Column (1) compares unconditional hazard; column (2) adds state and origination year fixed effects, lender, and macroeconomic controls; column (3) adds hard risk metrics and mortgage characteristics; and column (4) adds pricing data. See the appendix for variable definitions. Coefficient estimates are expressed as exponentiated (nonnegative) hazard ratios, with *t*-statistics reported below in parentheses. (Note that *t*-statistics are negative when the hazard ratio is less than 1.) All errors are clustered by lender. DV, dependent variable.

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

underwriting diligence. Second, homebuilders possessed greater soft information about homebuyers and local geographic conditions, which enabled better screening. Third, homebuilders internalized the costs associated with foreclosures on proximate homes, which led to more diligent underwriting. I focus on the 2005–2006 period for these analyses since differences between lenders were insignificant between 1999 and 2004, and, from 2007 onward, lending differences are

Table 3   Hazard of Mortgage Default by Time Period

	Hazard ratio (DV = *Notice of default*)			
	1999–2002 (1)	2003–2004 (2)	2005–2006 (3)	2007–2009 (4)
Stand-alone mortgage lenders	1.0887 (0.3290)	1.0623 (0.3849)	1.1401 (1.2348)	1.5023** (2.1561)
Depository banks	1.1917 (0.7791)	0.9968 (−0.0179)	1.3582*** (3.1618)	1.4641** (2.3605)
Affiliated mortgage lenders	0.9185 (−0.3786)	1.2590 (1.3555)	1.5643*** (4.7859)	1.3338 (1.3179)
Misc lenders	1.0303 (0.0823)	1.1416 (0.3972)	1.3359** (2.0772)	1.7956* (1.7882)
Observations	29,593	46,830	83,201	51,920
Pseudo *R*-squared	0.085	0.075	0.069	0.081

Notes. This table examines the relative hazard of mortgage default over time, with homebuilders as the omitted category. All models include geographic, risk, contract, and pricing controls from Table 2, column (4), as well as state and year fixed effects. See the appendix for variable definitions. Coefficient estimates are expressed as exponentiated (nonnegative) hazard ratios, with *t*-statistics reported below in parentheses. (Note that *t*-statistics are negative when the hazard ratio is less than 1.) All errors are clustered by lender. DV, dependent variable.

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

fully explained by firms that failed by the end of 2008, reflecting the highly abnormal industry conditions.[26]

4.1. Constrained Mortgage Holding Capacity
The argument for constrained holding capacity is as follows: Mortgage lenders use capital to fund and hold mortgages until the loans can be sold to third-party financial institutions. In general, institutional buyers have the option to reject (kick out) loans offered by the lender or to force the lender to repurchase (put back) loans if those loans were found to violate representations and warranties in the loan purchase agreements. Both actions would cause lenders to hold rejected loans until they could be sold. As a result, lenders with more limited holding capacity should exert more diligence during the underwriting process to minimize this mortgage holding risk. Under this scenario, homebuilders, following Stein's (1997, p. 113) loser-sticking argument, ration capital to their in-house mortgage units in order to provide resources to their land and construction operations, particularly during periods of high growth. Thus, we should observe homebuilder behavior consistent with constrained lending, especially during peak periods.[27]

[26] I define *failure* as an announcement closure of operations recorded by http://ml-implode.com/ or of government-backed injection of capital. Overall, 40% of the firms coded for this analysis failed by the end of 2008, accounting for 28% of the loans issued after 2006. Among stand-alone mortgage lenders, 51% of loans issued after 2006 were underwritten by firms that failed by the end of 2008. The coefficient on stand-alone mortgage lenders is explained entirely by firms that failed by the end of 2008. Mortgage lenders that survived beyond 2008 have a default hazard indistinguishable from homebuilders.

[27] A question that may arise is whether homebuilders could manage the kick-out problem by adjusting wholesale pricing rather than loan

Table 4   Median Housing (Land Purchase, Improvement, and Construction) Cash Flows Relative to Mortgage Unit

	Median housing cash flow/firm net income	Median mortgage unit cash flow/ firm net income	Median mortgage unit cash flow/ housing cash flow
All years	1.2697	0.0348	0.0518
1999	1.3519	0.2569	0.1198
2000	1.5346	0.0681	0.0534
2001	0.8864	0.3239	0.2164
2002	0.8600	0.3276	0.3573
2003	0.8933	0.0572	0.0658
2004	1.1886	0.0300	0.0018
2005	1.4419	0.0388	0.0349
2006	1.9384	0.0696	0.0432
2007	−0.3169	0.0000	−0.0887
2008	—	—	—
2009	—	—	—

Notes. Cash flow/net income is calculated as a two-year rolling measure and is set to 0 for negative net income years (therefore, 0 for all firms in 2008 and 2009). Data include all public homebuilders for which information was available in 10-K filings: Centex, D.R. Horton, Hovnanian, Lennar, Richmond American Homes, Pulte, Standard Pacific, and TOUSA. The top column is not two-year smoothed but annual calculations.

Although capital rationing is not directly observable, the reported cash flows of public builders provide some support for this argument. Table 4 shows the median cash flow allocated between land purchase, improvement, and construction ("housing") operations and the mortgage units within the eight public homebuilders for which data were available. The first column shows that housing operations consumed more cash than was generated through the internal operations of the firm, with the median cash flow allocated to housing across all years of the sample comprising 127% of net income. Over time, the allocation of cash to housing operations increased from 86% of net income at the economic trough in 2002 to 194% in 2006. The second column shows cash flow allocated to the mortgage units, with a median level of 3.5% of net income, far below the levels allocated to housing operations. In contrast to housing cash flow, cash flow to mortgage units generally decreased over the housing cycle. In 2006, mortgage units consumed the cash equivalent of 7% of net income, down from 33% in 2002. The final column shows the ratio of cash allocated to mortgage units as a percentage of cash allocated to housing operations, which shows the same countercyclical pattern.

These patterns are consistent with housing operations receiving relatively more capital as the boom progressed

quality. Unfortunately, I do not have wholesale pricing to investigate this channel. However, it is unlikely to be a large factor for two reasons: First, lowering loan prices would be unlikely to speed disposition since speed was related to originator reputation for quality, and high prices (rather than low) signaled quality (assuming, over the long run, that high prices reflect quality underwriting, the focus on this test). Second, if we assume that this channel does play some role, and price effects would offset quality, we can interpret the results in Table 5 as net of any price effect.

(the "winners" of the internal capital markets) and mortgage units receiving relatively less (the "losers") and, thus, becoming more constrained. This conclusion must be caveated as follows: since cash flow only measures absolute cash allocation and not allocation relative to investment opportunities, it is an imperfect measure of constraints. Conservatively, then, this table is consistent with, but not proof of, loser-sticking of the homebuilder mortgage units.

Two challenges also exist in testing whether these constraints affected lending quality: causal identification and measurement of mortgage holding capacity in a standard way across lenders with widely varying reporting requirements. In terms of causal identification, the ideal test would be to observe an exogenous shift in firms' mortgage holding capacities, followed by a corresponding change in lending quality. However, no such experiment occurred during this period. Therefore, the relation between holding capacity and lending quality is associative. Any causal interpretation is based on insight from practitioner interviews and ruling out alternative explanations.

Second, since I do not observe mortgage holding capacity, I construct two measures as proxies. The first is a direct calculation of the average loan holding period by firm using hand-collected data from public filings (SEC quarterly and annual 10-Q and 10-K filings, bank "call reports," and securitization prospectuses).[28] The second measure is the degree to which loans are priced on observable, hard information loan characteristics such as credit scores and loan-to-value ratios. Rajan et al. (2014) show that, to price and purchase mortgages as the boom progressed, both securitizers and investors of mortgage-backed securities increasingly relied on hard (verifiable) information and less on soft (unverifiable) information about the borrower.[29] Hard information is easy to observe and contract upon; therefore, mortgages underwritten and priced on hard information could be placed more quickly with third parties in secondary market sales. Consistent with this research, I interpret a firm's greater reliance on hard information for mortgage pricing as a proxy for its intent to sell mortgages quickly on the secondary market.[30]

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[28] The details of the data gathered and the holding-period calculation can be provided on request.

[29] Examples of hard information include the controls in Equation (1), whereas unverifiable soft information might include a loan officer's assessment of an applicant's credibility, her future employment prospects, and intuition about her likelihood of defaulting.

[30] Another potential interpretation of this proxy is that pricing *R*-squared represents the degree of soft information available to the lender; however, that would yield the opposite prediction and is not confirmed in the data. I thank an anonymous reviewer for pointing this out.

Table 5   Mortgage Holding Capacity and Hazard of Mortgage Default

	(A) Descriptive statistics			
	Homebuilders	Stand-alone mortgage lenders	Depository banks	Affiliated mortgage lenders
Mortgage holding period				
Mean (days)	19.12	28.46	44.41	61.13
SD	8.65	3.82	20.02	18.14
No. of (firms)	15	5	42	15
Pricing R-squared				
Mean	0.61	0.67	0.53	0.49
SD	0.06	0.11	0.14	0.17
No. of (firms)	29	114	79	37

	(B) Hazard of mortgage default, 2005–2006						
	Hazard ratio (DV = *Notice of default*)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mortgage holding period		1.0072***	1.0064***				1.0069***
		(3.2391)	(2.7460)				(3.0806)
Pricing R-squared					0.4753***	0.5794**	0.4194**
					(−3.0072)	(−2.2467)	(−2.5066)
Stand-alone mortgage lenders	1.0910		0.9512	1.1502		1.1536	0.8265
	(0.6096)		(−0.3806)	(1.3078)		(1.3266)	(−1.0292)
Depository banks	1.2767*		1.0267	1.3635***		1.2876***	0.9857
	(1.7854)		(0.1847)	(3.2111)		(2.7831)	(−0.1114)
Affiliated mortgage lenders	1.4644***		1.1551	1.6225***		1.5015***	1.0476
	(2.6615)		(0.8917)	(4.7484)		(4.1243)	(0.2283)
Observations	53,665	53,665	53,665	73,662	73,662	73,662	52,290
Pseudo *R*-squared	0.088	0.088	0.088	0.069	0.069	0.070	0.086

Notes. The *Misc lenders* category has been omitted because no data could be gathered on these lenders for this analysis. All models include geographic, risk, contract, and pricing controls from Table 2, column (4), as well as state and year fixed effects. See the appendix for variable definitions. Coefficient estimates are expressed as exponentiated (nonnegative) hazard ratios, with *t*-statistics reported below in parentheses. (Note that *t*-statistics are negative when the hazard ratio is less than 1.) All errors are clustered by lender. DV, dependent variable.

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

This proxy, pricing *R*-squared, is calculated by running one regression per firm of the mortgage price on the contract and macroeconomic characteristics described in Equation (1) and extracting the adjusted *R*-squared. Because of the requirement for sufficient numbers of mortgages and mortgage defaults to calculate both the *R*-squared and the hazard by lender, only the 241 most active firms could be used for this analysis.

The adjusted *R*-squared is extracted from running the following model for the *j*th firm:

$$price_i = \alpha_j + \beta_{j1} Macro_i + \beta_{j2} Lender_i$$
$$+ \beta_{j3} Risk + \beta_{j4} Contract_i + \beta_{year} YearFE_i$$
$$+ \beta_{st} StateFE_i + \varepsilon_i. \qquad (2)$$

Following Rajan et al. (2014), I use the initial rate of the loan for the price.[31] The holding-period measure and the explained pricing measure complement each other as proxies: the average loan holding period is

[31] The results are essentially unchanged when I rerun this analysis with only adjustable-rate mortgages and use the margin charged over the floating index once the teaser period expires.

subject to an ex post bias since the holding period may increase as loan quality decreases, whereas the explained pricing measure is unbiased by ex post performance but is, at best, an indirect proxy for capacity constraints.

4.2. Results
Panel (A) in Table 5 shows the descriptive statistics for the holding-period measures. Overall, the average holding period for homebuilders and stand-alone mortgage banks is 19.12 and 28.46 days, respectively, and 44.41 and 61.13 days for depository banks and affiliated mortgage lenders. These holding periods are statistically different from each other and consistent with homebuilders and stand-alone mortgage lenders funded by limited credit lines. Panel (A) also shows summary statistics for the pricing *R*-squared measure. The reasonably high negative correlation (−0.4071) between the mortgage holding period and pricing *R*-squared provides some confirmation that these measures, calculated from different sources and spanning different subsamples, capture similar underlying factors.

Panel (B) in Table 5 presents the association between the mortgage holding period and relative default hazard. Column (1) shows the relative hazard by parent

Figure 2   Firm-Level Hazard of Mortgage Default by Measures of Mortgage Holding Period
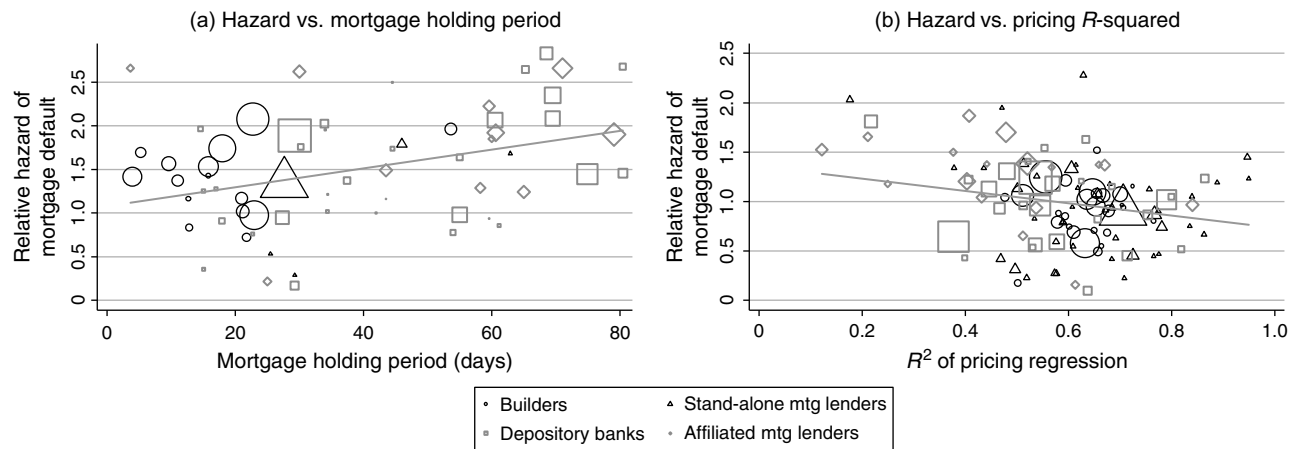
Notes. See panel (A) in Table 5 for mortgage holding descriptive statistics. Panel (a) shows hazard versus calculated mortgage holding period. Panel (b) shows hazard versus the R-squared of a firm-by-firm regression of pricing on observable mortgage characteristics (see Equation (2)). Hazard is calculated by extracting the coefficient on a firm dummy in a specification that replaces firm dummies for lender type dummies in Equation (1).

affiliations for the subset of firms for which the mortgage holding period was available. This subsample covers 72% of the mortgages issued for coded (nonmiscellaneous) lenders between 2005 and 2006 and includes public homebuilders and mortgage lenders, federally regulated banks, and firms that issued securitizations during the period.[32] Column (2) shows a significant association between the mortgage holding period and default hazard, with an increase in the holding period from the 10th percentile to the 90th percentile associated with a 28% increase in default hazard.

Column (3) presents one of the main results of this paper. It includes both holding period and parent affiliation indicators and shows that the holding period explains the differences in the relative default hazard between lender types. The coefficients on the parent affiliation indicators are now insignificant, whereas the coefficient on the mortgage holding period is 1.0064 and significant at the 1% level. An unreported analysis shows that the reductions in coefficients on the parent affiliation indicators between columns (1) and (3) are statistically significant.[33] Columns (4)–(6) replace the mortgage holding period with the pricing R-squared measure in the same analysis.[34] The point estimates and significances on the parent affiliation indicators are reduced substantially when the pricing R-squared

proxy is included in the models, although it does not explain all the differences between parent affiliations.[35]

Figure 2 presents results from a related analysis at the firm level, rather than at the individual mortgage level. In this analysis, firm-level measures of lending hazard are calculated by replacing lender affiliation indicators with individual lender identifiers in the hazard model for 2005–2006 (as shown in Table 3, column (3)). These firm-level hazard measures are plotted versus the two measures of holding capacity. The results confirm the findings in Table 5. Figure 2(a) shows a strong positive association between the mortgage holding period and firm-level hazard, and Figure 2(b) shows a strong negative association between pricing R-squared and firm-level hazard.

Overall, these analyses show that the differences in default hazard between lenders with different parent affiliations are explained by differences in mortgage holding capacity, as measured both by mortgage holding periods and by the degree to which loans are priced on hard information.[36]

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[32] The sample excludes primarily nonsecuritizing private stand-alone lenders and nonfederally regulated banks.

[33] Using STATA's *suest* command with a logit specification, I calculate the significance of the change in the coefficient estimates to have Pr > 0.0398, 0.0223, and 0.0253 for stand-alone mortgage lenders, depository banks, and affiliated mortgage lenders, respectively.

[34] This second subsample covers 99% of all coded (nonmiscellaneous) lenders, with the bottom 1% excluded because of insufficient degrees of freedom in the first-stage pricing regression.

[35] Using the *suest* command with a logit specification, I calculate the significance of the change in the coefficient estimates to be Pr > 0.6087, 0.1004, and 0.0372 for stand-alone mortgage lenders, depository banks, and affiliated mortgage lenders, respectively.

[36] These results at first may seem hard to reconcile with the high (13.65%) aggregated default rate of stand-alone mortgage lenders. The high default rate in Table 1 can be explained by a higher concentration of these lenders in riskier geographies and specialization in customers with higher credit risk and riskier contract structures. Once these "hard" metrics are accounted for, however, I find that underwriting diligence is higher than depository banks. This finding is consistent with Carey et al. (1998), who show that specialized lenders focus on riskier segments and compensate with reputations for tougher underwriting and loan management.

Table 6   **Information Tests**

| | Hazard ratio (DV = *Notice of default*) | | | |
| | Customer | | | Geography |
Risk measure =	*FICO* (1)	*CLTV* (2)	*Initial interest rate* (3)	*Peak to trough* (4)
Homebuilder	0.7106*** (−2.9753)	0.3729*** (−6.0065)	0.6542*** (−3.1998)	0.4642*** (−4.2783)
Homebuilder × Second quartile	0.9890 (−0.2045)	1.7418*** (4.8769)	1.0546 (0.9600)	1.3961** (2.0904)
Homebuilder × Third quartile	1.0338 (0.5693)	1.8280*** (5.5969)	1.0717 (1.1892)	1.5771*** (3.0437)
Homebuilder × Top quartile (most risky)	1.0658 (0.4753)	1.8742*** (5.2421)	0.9520 (−0.4328)	1.4511** (2.1663)
Second quartile	1.5699*** (13.8014)	1.3320*** (4.5173)	0.9346 (−1.4814)	1.3129*** (3.6666)
Third quartile	1.9029*** (14.8604)	1.9943*** (9.8727)	1.2444*** (4.2615)	2.7452*** (13.1953)
Top quartile (most risky)	2.5391*** (13.5234)	3.0934*** (17.2388)	2.0622*** (8.2427)	2.7414*** (12.2932)
Observations	72,052	83,201	83,201	83,201
Pseudo *R*-squared	0.067	0.064	0.064	0.061

Notes. FICO quartiles are reverse-scored, so that *top quartile* refers to the lowest (riskiest) quartile of FICO scores. *Peak to trough* is a measure of the difference between the peak home prices in a given county and the subsequent trough, from home price indices calculated by the author by using chained sales within each county in the data set. Column (1) excludes mortgages with missing FICO scores. All models include geographic, risk, contract, and pricing controls from Table 2, column (4), as well as state and year fixed effects. See the appendix for variable definitions. Coefficient estimates are expressed as exponentiated (nonnegative) hazard ratios, with *t*-statistics reported below in parentheses. (Note that *t*-statistics are negative when the hazard ratio is less than 1.) All errors are clustered by lender. DV, dependent variable.

   ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

4.3. Soft Information

The second possible explanation for lender differences is that homebuilders possess more "soft" information on the quality of both the borrowers and the local real estate market as a by-product of the home sales and land purchase process. They then use this information to screen borrowers more diligently, particularly in areas that they anticipate would be more affected by the housing downturn.[37]

This argument implies two sets of predictions. First, the difference in default hazard between homebuilder loans and those from other lenders should be greater within the consumer segments for which soft information is more important for determining default risk—that is, observably riskier consumer segments (Rajan et al. 2014).[38] Second, the difference in default hazard between homebuilder loans and those from other lenders should be greater in geographies that

experienced greater downturns after 2006 (such as Las Vegas, Phoenix, and Miami relative to Houston, for example, which experienced a negligible downturn in 2007). This latter prediction assumes that the broader market did not anticipate the severity of the downturn; therefore, homebuilders' superior local market knowledge would benefit them most in the hardest-hit areas.

4.3.1. Results. The results for tests of these two predictions can be found in Table 6. For the tests of superior soft information about homebuyers, I calculate quartiles for three of the most common observable risk measures—FICO score, combined loan-to-value ratio, and interest rate—with higher quartiles indicating higher risk.[39] These quartile indicators are then interacted with the homebuilder affiliate indicator. If homebuilders' use of soft information increases in riskier consumer segments, then the difference in relative hazard between homebuilders and all other lenders should be greater in riskier quartiles (the coefficients on the homebuilder × risk quartile interactions should be less than 1 and significant for higher-risk quartiles). The results can be seen in columns (1)–(3).[40] None of the interaction variables is significant in columns (1)

[37] Note that we would have to make additional assumptions about homebuilders' profit functions or secondary market sales to explain why they would choose to apply more diligent screens than their peers, even with free information. For simplicity, we assume that this is the case.

[38] In an unreported analysis, I verified the connection between soft information and observable risk directly by regressing price versus observables by FICO decile and find that the *R*-squared for the lowest (riskiest) decile is 0.1537 and the *R*-squared for the highest (least risky) decile is 0.3048.

[39] Consequently, the FICO quartiles are reverse-scored.

[40] The difference in the sample size in column (1) reflects the fact that the FICO score was not available for all mortgages.

and (3). In column (2), the interactions are greater than 1 and significant, indicating that homebuilder loans were particularly safer in the lowest (safest) quartile of CLTV. Although this result is the opposite of our prediction, the interactions in the second, third, and fourth quartiles are not significantly different from each other, indicating no clear relationship between risk and decreased relative hazard between homebuilders and financial lenders.

To test for superior local real estate market knowledge, I measure the difference between peak home prices and the subsequent trough post 2006 in each county of the analysis, using the home price index constructed from chained home sales reported in the county deed data. As peak-to-trough distance increases, the difference in relative default hazard between homebuilders and other lenders should increase if homebuilders anticipated the downturn better than their competitors. As with the prior tests, I produce quartiles of the peak-to-trough measure and create interactions with the homebuilder indicator. The results are reported in column (4). As with the CLTV result in column (2), the interactions are greater than 1 and significant, indicating that builder loans were particularly safer in the least risky geographies. However, also like column (2), the interactions in the second, third, and fourth quartiles are not significantly different from each other, indicating no clear relationship between risk and decreased relative hazard between homebuilders and financial lenders. In short, unlike the prediction for this test, I do not observe any divergence in the hazard ratio between homebuilders and financial lenders as the risk quartile increases.

This discussion must include the caveat that the null results may be a function of the test design and measures used. An ideal test, such as the random assignment of soft information across lenders, did not occur in this context. Conservatively, therefore, the results of these tests do not support soft information explanations, but they do not rule them out.

4.4. Foreclosure Externalities

Another explanation for higher lending quality is that homebuilders lent more safely because they internalized the costs of foreclosures within their subdivisions, and other lenders did not. Since World War II, the majority of new homes have been constructed within residential subdivisions that can include thousands of homes (Duany et al. 2000). These subdivisions may require multiple years or decades to sell completely and can have high construction density, so homebuilders assume substantial land and home inventory risk that increases as foreclosures increase in the area. Since financial lenders are not precommitted to subdivisions, they do not internalize these foreclosure costs. The cost of foreclosure externalities has been shown to be quite

large: Campbell et al. (2011) estimate a 1% reduction on the prices of homes within 0.05 miles of a foreclosure and effects up to 0.25 miles.

I develop two predictions based on this result of Campbell et al. (2011). First, within subdivisions, foreclosures of homes sold earlier in the life cycle should be costlier to homebuilders than homes sold later since they affect demand and prices on a greater number of future homes. All else equal, therefore, homebuilders should be relatively more diligent with earlier sales than with later sales. This test assumes that homebuilders have foreknowledge of the construction life cycle within a subdivision.[41] Second, the cost of foreclosures should be relatively greater in more densely constructed subdivisions. Therefore, homebuilders' relative lending diligence should be greater in those subdivisions, whereas these patterns should not be observed in financial lenders.

To test these predictions, I compute order and density measures using census block groups as a proxy for subdivisions, which cannot be observed. Census block groups are an intermediate measure between census tracts and census blocks, the smallest unit used by the U.S. Census that can map to individual street blocks. These measures are calculated on a premerged database of 697,456 loans to increase the number of observations within each census block group.[42] Each zip code contains a median of 13 census block groups.

I construct a measure of the order of loans issued by the lender in a given census block group over the sample period, normalized from 0 (earliest) to 1 (latest). I then create the density measure as the sum of all mortgages in a census block group for a given lender over the sample period.[43] Finally, I calculate quartiles of these measures and create interactions with the homebuilder indicator. The prediction is that the differences in relative hazard between homebuilders and financial firms should be greater in earlier and denser quartiles; therefore, the coefficients on the interactions between homebuilder and earlier and denser quartiles should be less than 1 and significant.

As a robustness test, I also use a subsample of mortgages that includes only homes constructed by homebuilders with lending units. I then recreate order

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[41] This assumption seems reasonable in this context since homebuilders' community development plans typically include detailed development schedules of the subdivisions, including multiple development phases that span years and assign sites of future homes to specific phases.

[42] This premerged database includes mortgages that include conventional FHA/VA loans for new construction single family and multifamily homes and condos.

[43] Note this is not a perfect measure of density since not all census block groups are the same geographic size. However, given the exurban composition of the data set, I assume that it is a reasonable proxy.

Table 7   Foreclosure Externality Tests by Quartile

	Hazard ratio			
	Lending order[a] (1)	Lending density (2)	Construction order[a] (3)	Construction density (4)
Homebuilder	0.7686***	0.5523***	0.6638***	0.6449***
	(−3.0622)	(−3.1973)	(−4.4360)	(−5.2676)
Homebuilder × Second quartile	0.9142	1.3796*	0.9907	1.0770
	(−1.5310)	(1.8183)	(−0.1505)	(0.7595)
Homebuilder × Third quartile	0.9190	1.5078**	1.0249	1.0320
	(−1.1876)	(2.3464)	(0.3990)	(0.4710)
Homebuilder × Top quartile (most externalities)	0.9242	1.4922**	1.0983	1.0369
	(−0.8958)	(2.1267)	(1.2019)	(0.3355)
Second quartile	1.0302	0.8969**	0.9609	1.1204*
	(0.8758)	(−2.4448)	(−0.9941)	(1.7678)
Third quartile	1.0463	0.8476**	0.9498	0.9227
	(1.0270)	(−2.2910)	(−1.4379)	(−1.6301)
Top quartile (most externalities)	1.0708	0.7314***	0.9754	0.9479
	(0.9948)	(−5.1679)	(−0.5155)	(−1.0334)
Observations	82,996	82,996	51,294	51,294
Pseudo *R*-squared	0.069	0.069	0.072	0.072

Notes. Lending order refers to the order of loans issued by a lender within a census block group (as a measure of future foreclosure risk) and has been reverse-coded so that higher quartiles refer to earlier lending (and, hence, greater potential externalities). *Lending density* refers to the number of loans by a given lender within a census block group (a measure of loans exposed to foreclosure costs). *Construction order* refers to the order of construction by a homebuilder within a census block group (as a measure of future foreclosure risk) and has been reverse-coded so that higher quartiles refer to earlier construction (and, hence, greater potential externalities). *Construction density* refers to the number of homes constructed by a homebuilder within a census block group (measure of number of homes exposed to foreclosure costs). Specifications using these measures include only homes constructed by homebuilders with in-house lenders and compare in-house loans versus loans made by outside lenders. All models include geographic, risk, contract, and pricing controls from Table 2, column (4), as well as state and year fixed effects and include mortgages issued between 2005 and 2006. See the appendix for variable definitions. Coefficient estimates are expressed as exponentiated (nonnegative) hazard ratios, with *t*-statistics reported below in parentheses. (Note that *t*-statistics are negative when the hazard ratio is less than 1.) All errors are clustered by lender.

[a] Reverse-coded.

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

and density measures by construction order and density rather than by lending order and density. This approach arguably controls for more subdivision unobservables in exchange for fewer observations.

4.4.1.   Results. Table 7 shows the results of these tests. In column (1), none of the interactions between homebuilder and lending order is significant, suggesting that concern for future foreclosures does not drive safer earlier lending practices by homebuilders. Similarly, in column (2), the interactions between homebuilder and lending density are significant and greater than 1, suggesting that homebuilder loans had the lowest relative default hazard in the least dense census block groups, the opposite of our prediction. However, the interactions between homebuilder and the second, third, and fourth quartiles are not significantly different from each other, indicating that there is not a strong relationship between lending density and lower relative hazard between homebuilders and financial lenders. Columns (3) and (4) show no significant interactions between homebuilders and order or density.

Similar to the caveat for the test for soft information, I cannot rule out that the null result in these tests is due to the test design and measures used. One issue is

that subdivision density is nonrandom and unobserved attributes of these subdivisions may cause results that cancel out this test.[44] An ideal test to identify this channel would involve randomization of the expected costs of foreclosure externalities, potentially by reassigning land and homes under construction within the same subdivision to other developers. These types of treatments are not particularly realistic, but without them, the results of the actual tests performed do not provide causal identification. Conservatively, therefore, they do not support foreclosure externalities as drivers of lending restraint, but they do not rule them out.

5.   Other Possible Explanations
There are several other possible explanations for differences between lenders. One possibility is that depository banks were subject to additional regulation requiring them to devote a certain percentage of their mortgage portfolio to low-income consumers and that

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[44] For example, if homebuilder inventory is greater relative to demand in denser subdivisions, then homebuilders may have a greater incentive to screen consumers less diligently in these divisions in order to move inventory.

these loans drove the differences between banks and other lenders. In fact, the Community Reinvestment Act of 1977 (CRA) has been shown to lead to poor-quality loans by banks (Agarwal et al. 2012). However, this regulation is unlikely to have influenced the results in this study since the sample consists of high-growth suburban and exurban zip codes that probably did not include many CRA loans. As a check, unreported analysis shows that lending differences do not diminish when excluding the bottom of the home price distribution, the segment most likely to include CRA loans.

A second possible explanation is that banks and affiliated mortgage banks had access to lower-cost funds than other lenders, enabling them to lend to relatively riskier consumers profitably. This explanation, however, is inconsistent with the time history in the federal funds effective rate over the study period. The federal funds effective rate steadily declined from a high of 6.53% in June 2000 to 0.99% in March 2004 and then increased from 5.23% to 5.24% between July 2006 and August 2007. If lower cost of available federal funding to banks drove relatively worse lending, we would expect to see relatively worse bank lending during the earlier period in the sample, followed by a relative increase in banks' lending standards as the federal funds rate increased in 2004. We observe the opposite.

A third possible explanation is that multiproduct pricing by homebuilders drives differences in loan outcomes. Although mortgage/home cross-subsidization is quite plausible in this context, it is unlikely to lead to the results in this paper (i.e., safer homebuilder loans, conditional on observables). First, we would have to believe that homebuilders used the housing operations to subsidize mortgage lending rather than the reverse, which is not plausible in this context.[45] Second, unreported results show that homebuilders actually offered lower loan rates than financial lenders, which is inconsistent with the multiproduct pricing alternative and consistent with more conservative screening.

A final possible explanation is that homebuilders show more forbearance than other lenders in filing notices of default. However, given that servicing rights were typically sold at the same time as the mortgage, this explanation would not explain differences in default rates.

6. Discussion and Conclusion

This paper shows that loan quality during the years preceding the 2007 housing crisis was, in fact, related to the mortgage lenders' parent affiliation. Lending standards of homebuilders and stand-alone mortgage lenders deteriorated significantly less than those of

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[45] That is, we would have to believe that homebuyers would accept lower home sale prices or other in-kind benefits on the home in exchange for worse loan terms and higher loan rates.

depository banks and mortgage lenders affiliated with large financial institutions. This result is surprising for several reasons. It is contrary to prior models and empirical studies of captive finance (Barron et al. 2008, Pierce 2012). Also, both homebuilders and stand-alone mortgage lenders are originate-to-distribute lenders; that is, they originate loans with no intent to retain them on their balance sheets and therefore have little skin in the game. Prior research has suggested that having little skin in the game encouraged lenders to underwrite poor-quality loans (Purnanandam 2011, Demiroglu and James 2012).

To understand this result, I investigate three possible explanations and find evidence consistent with one—namely, that lenders with limited mortgage holding capacity engaged in higher screening than less con-strained lenders. I argue that constrained lenders were particularly affected by market diligence since even a moderate level of mortgage rejections by institutional buyers could absorb already scarce capacity and impair their ability to issue new loans. The analysis supports this explanation: the inclusion of mortgage holding capacity proxies in the main specification is sufficient to explain the default hazard differences between lenders. Furthermore, moving from the 10th to 90th percentile in mortgage holding capacity is associated with a 28% increase in loan default hazard. The constraints explana-tion is also consistent with reported cash flows within homebuilders. As the housing boom progressed, home-builders allocated relatively more capital to housing operations and less to mortgage units. These cash flow patterns are in turn consistent with practitioner inter-views who stated that they allocated as little cash to lending as possible in order to invest as much capital as possible into land and construction during this period. I also investigate whether differences in access to soft information or incentives to avoid foreclosures explain lending quality differences and find no evidence in support of either factor.

This study has several limitations. First, mortgage unit constraints cannot be measured directly, given the diversity of firms and reporting requirements in the sample. Therefore, the study relies on proxies for the analysis. Second, formal causal identification cannot be established: the tests for lending constraints are correlative, and so the research design relies on ruling out alternative explanations. This design presents two related challenges: loan quality, interest rates, and mortgage holding period may be simultaneously determined by an unobserved factor, and therefore the causal chain presented in the paper may not be valid. Also, the null findings from tests of these alternatives may be a function of the tests rather than evidence of the absence of effect in this setting. In fact, it is entirely plausible that multiple factors affecting lending may have been simultaneously present in this setting. Finally, although the evidence is consistent with the

mortgage units' becoming increasingly constrained over time, the available data do not enable a direct test of constraints.

Despite these challenges, the findings of this study have implications for both strategic management and corporate finance. Specifically, the results suggest an interesting relationship among firm boundaries, internal capital markets, and strategic adaptation that merits further exploration. I speculate on the relationship as follows: A well-known feature of internal capital markets, as discussed by Stein (1997), is that managers "winner-pick" projects; that is, they direct funds to divisions of their choice above levels available from external markets. A necessary, but less explored, consequence of winner-picking is what Stein calls loser-sticking. That is, to fund winners, managers must withhold funds from other projects, even if those projects are net present value-positive and would otherwise be funded by external markets. Since firm boundaries define the set of projects that are ranked relative to each other, boundaries influence whether a business unit (equivalent to a project for this discussion) is well funded or resource constrained. Resource constraints, in turn, drive different behavior in end markets, including how firms adapt to shifts in the external environment.

In this study, although the association cannot be observed directly, evidence from public homebuilders' cash flow statements supports the idea that mortgage units were loser-stuck during this period: as the housing boom progressed, the mortgage units received a decreasing proportion of cash relative to the housing operations. Furthermore, unreported analyses show that mortgage units received a lower share of cash relative to housing operations as homebuilders' revenue and earnings increased. I propose that, as the boom progressed and these units received fewer resources, they responded by exerting relatively more diligence than their less constrained financial counterparts.

The findings of this paper suggest a larger research agenda on the effects of firm scope on internal capital and labor markets. To the extent that we can interpret looser diligence as evidence of agency problems within firms, then loser-sticking may mitigate these issues by exposing firms to greater market discipline. Aside from greater discipline, loser-sticking may have other consequences for firm adaption. For example, it may influence how these secondary units innovate, choose their product lines, or otherwise respond to competition. Firm scope may also have effects on internal labor markets analogous to those on capital markets, with "loser" units attracting different talent than would be available to otherwise identical nonintegrated units, or "winner" units, in different firms. Winner-picking may also have similar-magnitude effects on adaptation.

In sum, this research proposes a different approach to Coase (1937)'s question on the nature of firms and markets. By applying the concept of winners and losers in internal capital (or labor) markets to organizational strategy, the paper speculates that firm boundaries matter because they affect not only transaction costs and property rights but also resource endowments.

Appendix. Variable Definitions

Variable	Definition	Source
Notice of default	A notice filed in the county public record that the borrower has officially defaulted on the mortgage; this notice is considered the first step in foreclosure proceedings	Public records
Sale amt ($)	Sale price appearing on the recording document	Public records
Mtg amt ($)	Amount of the mortgage, first-lien only	Public records
Initial interest rate	Original or initial interest rate as of the loan's first payment date	Servicing database
Margin	Basis points added to the ARM index to determine the coupon rate of the ARM loan	Servicing database
CLTV	Ratio of the first and second lien amount to the sale price of the house at the time of purchase	Public records
FICO	FICO (credit) score of the borrower at the time of loan origination	Servicing database
Low or no documentation	Indicator equal to 1 if loan documentation was not complete	Servicing database
Back-end DTI	The total monthly liabilities of the borrower, including the debt on the subject property, divided by the total monthly income of the borrower(s)	Servicing database
Adjustable rate mortgage (ARM)	Indicator equal to 1 if the mortgage rate is determined by a spread over a floating index	Servicing database
Fixed rate mortgage (FRM)	Indicator equal to 1 if the mortgage rate is determined by a fixed coupon rate	Servicing database
Hybrid rate mortgage	Indicator equal to 1 if mortgage rate is determined by an initial fixed rate, followed by adjustable rate	Servicing database
Balloon mortgage	Indicator equal to 1 if mortgage rate is determined by an oversized payment at maturity	Servicing database
Negative amortization	Indicator equal to 1 if the mortgage has a provision that allows monthly payments below the interest coverage amount, rolling the difference into the principal balance	Servicing database
Interest only	Indicator equal to 1 if the mortgage has a provision that allows monthly payments to cover only interest owed, rather than interest plus amortization of the loan balance	Servicing database
Prepayment penalty	Indicator equal to 1 if the mortgage has a provision that assesses a penalty to the borrower if a loan is prepaid	Servicing database
Log tract 2000 med inc	Median income of households within a census tract in 2000	Census Bureau
Freddie 30-yr rate	Interest rate for 30-year fixed mortgages published by Freddie Mac	Freddie Mac
Fed Funds rate	The interest rate at which depository institutions trade balances held at the Federal Reserve	Federal Reserve

Appendix. (Continued)

Variable	Definition	Source
Regional home prices	A home price index at the county level constructed from the mortgages in this data set	Public records
State-level unemployment	Quarterly state unemployment rates	Bureau of Labor Statistics
Log annual number loans	Log of the number of loans originated by each lender within this data set	Public records
Lender independent	Indicator equal to 1 if the lender does not have a parent company	Researcher
Parent public	Indicator equal to 1 if the parent company is publicly traded	Compustat
Parent log assets	Log of the parent assets if the parent company is publicly traded	Compustat
Lender JV with bank	Indicator equal to 1 if the homebuilder's lending unit is a joint venture with a financial firm	Various

References

Agarwal S, Benmelech E, Bergman N, Seru A (2012) Did the Community Reinvestment Act (CRA) lead to risky lending? NBER Working Paper 18609, National Bureau of Economic Research, Cambridge, MA.

Barney J (1986) Strategic factor markets: Expectations, luck, and business strategy. *Management Sci.* 32(10):1231–1241.

Barron JM, Chong B-U, Staten ME (2008) The emergence of captive finance companies and risk segmentation of the consumer loan market: Theory and evidence. *J. Money, Credit Banking* 40(1):173–192.

Baysinger B, Hoskisson RE (1989) Diversification strategy and R&D intensity in multiproduct firms. *Acad. Management J.* 32(2):310–332.

Campbell JY, Giglio S, Pathak P (2011) Forced sales and house prices. *Amer. Econom. Rev.* 101(5):2108–2131.

Carey M, Post M, Sharpe SA (1998) Does corporate lending by banks and finance companies differ? Evidence on specialization in private debt contracting. *J. Finance* 53(3):845–878.

Coase RH (1937) The nature of the firm. *Economica* 4(16):386–405.

Dell'Ariccia G, Igan D, Laeven L (2012) Credit booms and lending standards: Evidence from the subprime mortgage market. *J. Money, Credit Banking* 44(2–3):367–384.

Demiroglu C, James C (2012) How important is having skin in the game? Originator-sponsor affiliation and losses on mortgage-backed securities. *Rev. Financial Stud.* 25(11):3217–3258.

Demyanyk Y, Van Hemert O (2011) Understanding the subprime mortgage crisis. *Rev. Financial Stud.* 24(6):1848–1880.

Donaldson G (1984) *Managing Corporate Wealth: The Operation of a Comprehensive Financial Goals System* (Praeger Publishers, New York).

Duany A, Plater-Zyberk E, Speck J (2000) *Suburban Nation: The Rise of Sprawl and the Decline of the American Dream* (North Point Press, New York).

Foote CL, Gerardi K, Goette L, Willen PS (2008) Just the facts: An initial analysis of subprime's role in the housing crisis. *J. Housing Econom.* 17(4):291–305.

Forbes SJ, Lederman M (2009) Adaptation and vertical integration in the airline industry. *Amer. Econom. Rev.* 99(5):1831–1849.

Hoskisson RE, Hitt MA, Hill CWL (1993) Managerial incentives and investment in R&D in large multiproduct firms. *Organ. Sci.* 4(2):325–341.

Jacobides MG, Winter SG (2005) The co-evolution of capabilities and transaction costs: Explaining the institutional structure of production. *Strategic Management J.* 26(5):395–413.

Keys BJ, Mukherjee T, Seru A, Vig V (2009) Financial regulation and securitization: Evidence from subprime loans. *J. Monetary Econom.* 56(5):700–720.

Keys BJ, Mukherjee T, Seru A, Vig V (2010) Did securitization lead to lax screening: Evidence from subprime loans. *Quart. J. Econom.* 125(1):307–362.

Lyandres E (2006) Strategic cost of diversification. *Rev. Financial Stud.* 20(5):1901–1940.

Macher JT (2006) Technological development and the boundaries of the firm: A knowledge-based examination in semiconductor manufacturing. *Management Sci.* 52(6):826–843.

Mayer C, Pence K, Sherlund S (2009) The rise in mortgage defaults. *J. Econom. Perspect.* 23(1):27–50.

Mian A, Sufi A (2009) The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *Quart. J. Econom.* 124(4):1449–1496.

Nickerson JA, Zenger TR (2008) Envy, comparison costs, and the economic theory of the firm. *Strategic Management J.* 29(13):1429–1449.

Pierce L (2012) Organizational structure and the limits of knowledge sharing: Incentive conflict and agency in car leasing. *Management Sci.* 58(6):1106–1121.

Piskorski T, Seru A, Vig V (2010) Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis. *J. Financial Econom.* 97(3):369–397.

Purnanandam A (2011) Originate-to-distribute model and the subprime mortgage crisis. *Rev. Financial Stud.* 24(6):1881–1915.

Rajan U, Seru A, Vig V (2014) The failure of models that predict failure: Distance, incentives and defaults. *J. Financial Econom.* Forthcoming.

Rawley E (2010) Diversification, coordination costs, and organizational rigidity: Evidence from microdata. *Strategic Management J.* 31(8):873–891.

Rawley E, Simcoe TS (2010) Diversification, diseconomies of scope, and vertical contracting: Evidence from the taxicab industry. *Management Sci.* 56(9):1534–1550.

Remolona EM, Wulfekuhler KC (1992) Finance companies, bank competition, and niche markets. *Fed. Reserve Bank New York Quart. Rev.* (Summer):25–38.

Seru A (2014) Firm boundaries matter: Evidence from conglomerates and R&D activity. *J. Financial Econom.* 111(2):381–405.

Shiller R (2008) *The Subprime Solution: How Today's Global Financial Crisis Happened, and What to Do About It* (Princeton University Press, Princeton, NJ).

Stein JC (1997) Internal capital markets and the competition for corporate resources. *J. Finance* 52(1):111–133.

Wernerfelt B (1984) A resource-based view of the firm. *Strategic Management J.* 5(2):171–180.

Williamson OE (1975) *Markets and Hierarchies: Analysis and Antitrust Implications* (Macmillan, New York).

Williamson OE (1985) *The Economic Institutions of Capitalism* (Free Press, New York).

Zhou MY (2011) Synergy, coordination costs, and diversification choices. *Strategic Management J.* 32(6):624–639.