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Did Increased Large Bank Concentration of US Mortgage Loan Originations Explain Rising Originator Profits?

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Concentration amongst the top 100 mortgage originators rose substantially during the Great Recession. Furthermore, Originator Profits and Unmeasured Costs (OPUCs), a proxy measure of the profit from originating residential mortgage loans also rose over the same period. Recent studies suggest that these increases are only partially explained by rational factors such as rising costs from increased regulatory burdens and changes in risk. We find statistically significant evidence that increasing concentration raised loan costs by 97 basis points using Vector Autoregressive (VAR) models during the Great Recession. This finding suggests that banks are exploiting increasing monopolistic power to increase profits and as such, consumers face rising costs as competition amongst lenders declines. Further to this issue, this study suggests that mortgage markets are not fully competitive and that the rates and fees charged to borrowers are in fact impacted by the level of competition amongst lenders.

Keywords

Banks (G21), Mortgages (G21), Size Distribution of Firms (L11), Real Estate Markets General (R30), Housing (O1)

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1. Introduction and Theory

The pricing and availability of mortgage loans have always been important components of the real estate system and areas of great study in the literature. Most of the literature and discussion on the topic focus on the interaction of the borrower with the lender and study the borrower as the central item of investigation. While borrower characteristics (income, demographics, credit score, etc.) are well known to impact mortgage pricing, especially those directly related to the determination of default risk, less is known about the role of the availability of lending options to the consumer in the determination of mortgage costs. This paper seeks to address this relatively less studied area of the mortgage literature by presenting an empirical investigation on the impact of increasing mortgage loan origination concentration by the largest lenders in the United States (US) before and during the "Great Recession". Using a measure of Originator Profits and Unmeasured Costs (OPUCs) developed by Fuster et al. (2013), we determine that rising rates of concentration in mortgage loan originations do in fact help to explain the rising rates in OPUCs after controls for other contributory factors are utilized. Specifically, we estimate that OPUCs[1] increased 0.93% from 2007 to 2011 as a result of rising origination concentration[2]. This nearly 1% increase in costs is highly economically significant and represents a burden placed on consumers as a result of reduced competition and monopolistic behavior by lenders.

During the "Great Recession", many lending institutions failed and then were sold or merged to form even larger institutions than before; as such, the number of potential mortgage originators in the primary market was necessarily reduced. Further to this issue, many of the largest banks increased their retail lending footprint via said mergers and acquisitions, also reducing potential for borrowers to shop for competitive loans and thus driving up the monopolistic power of these larger originators. Cheng et al. (2011) conclude that women pay more for mortgages because they fail to shop for the lowest rate at the same frequency of their male counterparts. Ambrose and Conklin (2014) find that increased competition amongst mortgage brokers by metropolitan statistical area leads to lower fees in both brokered loans and retail originations thus supporting the notion that competition lowers rates and costs for the borrower. Furthermore, Courchane (2007) while primarily studying pricing differentials paid by minority borrowers, finds that there is little evidence of differential treatment by lenders, instead differentials paid are primarily explained by the type of loan applied for and chosen (such as subprime). This factor is potentially influenced by competitive loan shopping and choice by the borrower. In fact, Berndt et al. (2016) investigate the role of brokers and competitive loan

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[1] Note that the OPUCs can be a combination of fees and interest rate costs charged to or paid by borrowers.

[2] The calculation is discussed in the results section and presented in Table 2 and Figure 9.

shopping in the subprime origination market and find that less informed borrowers shop less for loans and pay more in fees. LaCour-Little (2009), on the other hand, demonstrates that mortgage brokers cost borrowers an average of 20 basis points more for loans versus retail bank originated loans, but contributes this finding to poor incentive alignment between borrower and broker, not necessarily the competitive nature of shopping for a lender or broker. In a theoretical investigation, Ben-Shahar (2008) discusses the predicted behavior of borrowers and lenders in competitive and non-competitive mortgage markets; the study shows that the monopolistic power of lenders, which the author seems to believe is present, does impact the characteristics of the origination process including those likely to impact pricing and fees. Overall, the literature supports that shopping for loans reduces rates and fees paid, but generally examines the question from the standpoint of "did" the consumer shop or not. This study contributes to the literature by examining the competitive nature of mortgage originators and thus offers a deeper understanding of the forces, outside normal borrower credit quality analyses, that impact fees and costs in mortgage borrowing.

Utilizing Home Mortgage Disclosure Act (HMDA) data from 1993 through to 2011, we first find that the concentration amongst the top 100 mortgage originators in the US increased during the Great Recession that started at the very end of 2007. This increase in market share and origination concentration from 2007 onward was predicted by Calem and Follain (2007) as an expected impact of impending Basel II regulations; of course, tightening in the regulatory structure of lending institutions only intensified after 2007. Thus, this study provides an empirical test and validations to the theoretical findings of Calem and Follain (2007). Also following the financial turmoil of 2008, the spread between primary market lending rates and secondary market valuation/discount rates, a measure that proxies for the gross profits of mortgage origination, rose as well. Fuster et al. (2013) look at this issue and calculate a measure to better proxy for OPUCs. They conclude that a significant component of the rise in OPUCs cannot be explained by cost increases alone (such as those due to regulatory changes) and suggest increased profitability of the originators may be an explanation. Herein, we examine and empirically test whether the increased concentration amongst the largest 100 originators in the US explains the rise in OPUCs. If so, it suggests that mortgage originators increased profits as a result of increased monopolistic power and reduced borrower choice. Interestingly, Fuster et al. (2013) dismiss market concentration as the leading cause of the rise in OPUCs[3], and our analysis attempts to present a more rigorous test to this question.

The literature has historically found that increased concentration of lending and banking institutions leads to higher profit, usually at the direct cost of the

[3] Avery et al. (2012) also indirectly address the same issue.

borrower[4]. Furthermore, prior studies have also shown that when faced with times of higher economic uncertainty, lower aggregate borrower credit quality, and/or increased or changing regulatory environment, banks and lending institutions combine and increase market concentration as a way of protecting and growing profits[5]. Additionally, studies have specifically shown that recessions increase volatility[6] and that smaller financial institutions are relatively less able than larger ones to cope with such volatility and regulatory changes[7]. Our study broadly agrees with Scharfstein and Sunderam (2013), who analyze lending patterns across multiple countries and conclude that increased credit concentration can lead to higher spreads between primary mortgage originations and secondary market transactions.

Thus, this paper sets out to examine credit concentration and its effects on the profits of mortgage lenders, as proxied by the OPUCs. To accomplish this, we first test whether credit concentration among large participating lenders rose during the Great Recession (Hypothesis I). Second, we investigate the determinants of credit concentration in the mortgage market. Third, we ask whether lender concentration created monopolistic power for large financial institutions, allowing them to increase interest rate spreads on their loans and thus achieving higher profits (Hypothesis II). We utilize the OPUCs as obtained and calculated by Fuster et al. (2013) as our proxy for profit. As will be explained in Section Two, OPUCs are an estimate of the profits of lenders net of observable costs. OPUCs are therefore likely the best available proxy for the profits of the originators who make loans in our dataset.

We find that that concentration did in fact increase in the top mortgage originators following the recession, and that this increased concentration increased the profits of lenders, potentially due to their increased monopolistic power. As such, borrowers are potentially worse off as a result of increased concentration of mortgage origination activities; a result with broad market and regulatory implications.

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[4] Mercieca et al. (2012), Neuberger et al. (2008), De Castro and Faymefr (2008), and Valvonis (2007).
[5] Godlewski and Ydriss (2010), Lee and Mullineaux (2004), and Lapteacau (2012).
[6] French and Sichel (1993) and Hamilton and Susmel (1994).
[7] Albertazzi (2007) states that economies of scale minimize costs; thus smaller institutions are more encouraged to combine during highly volatile periods.

2. Credit Concentration in the Banking Sector

2.1 Methodology

To empirically test the effect of the state of the economy on market concentration, we first construct the **Comprehensive Concentration Index (CCI)**. The CCI accounts for both absolute concentration and relative dispersion. Horvath (1970) defines the CCI as "the sum total of the proportional share of the leading firm plus the summation of the square of the proportional sizes of each firm reinforced by a multiplier reflecting the proportional size of the rest of the industry".

The CCI is defined as:

$$CCI_t = S_{i,t} + \sum_{i=2}^{n} (S_{j,t})^2 (1 + [1 + S_{j,t}]) \qquad (1)$$

where S_i is the largest fraction of the total loan amount provided by any lender (the absolute concentration). This lender is given the index 1, and excluded from the sum. Intuitively, the first term measures the absolute share of the leading lender and the second term measures the relative concentration of the remaining lenders. The CCI assigns a weight (2–S_j) to all non-leading lenders, so that lenders with very small shares have weights close to 2 and lenders with market shares similar to the leading lender have weights close to 1. The maximum value that the CCI can take is one in the case of a monopoly, and its minimum value is zero in the case of a large number of lenders with equal shares.

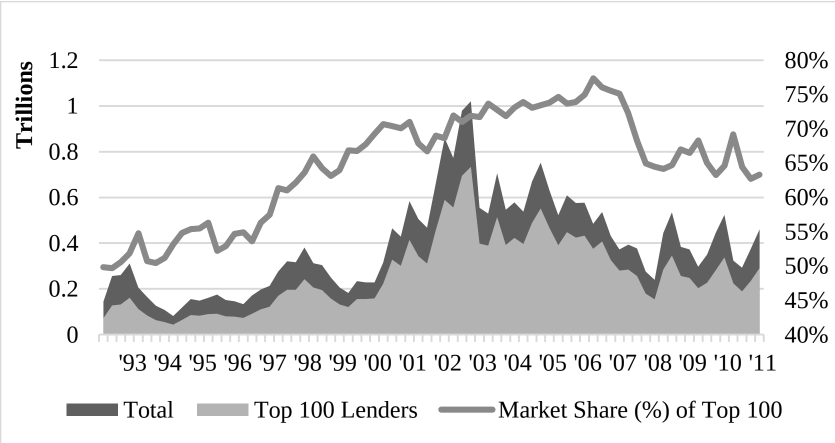
2.2 Data

The study uses the large Home Mortgage Disclosure Act (HMDA) dataset maintained by the Federal Financial Institutions Examination Council (FFIEC). Each home loan record includes the lender identity, loan amount, loan duration, and whether the loan was a new purchase or a refinance. We are especially interested in loans originated by the 100 largest originators, ranked in terms of the total dollar amount of all loans provided by each originator on an annual basis. For discussions on limitations and uses of HMDA data, see Avery et al. (2007) and LaCour-Little (2007).

2.3 Results for Empirical Studies

Figure 1 shows the total dollar volume of mortgage loans originated by the entire lending sector and the leading 100 originators from 1993Q1 to 2011Q4. The total amount increased slightly during the 1990s, began soaring in 2000, and peaked in 2003Q3. Lending then gradually declined, with large drops in 2003Q4 ($465 billion) and 2010Q1 ($372 billion). The number of loans followed the same trends. Loans from the top 100 originators accounted for 65% of the total dollar amount and 62% of the number issued over the entire sample period. Their share of the amount (number) increased gradually from 50% (47%) in 1993Q1 to 75% (73%) in 2007Q4. Following this peak, their share declined gradually to 63% (61%) by 2011Q4. Fuster et al. (2013) discuss market concentration by detailing how the market share of the top ten lenders rose and then fell from 2008 to 2012.

Figure 1 Origination Volume



In Figure 2, we see that the CCI was relatively stable in the 10-12% range from 1993 to 2000. During the 2001 recession, the CCI jumped to nearly 20% and stayed there until mid-2003 when it plunged to 15%. It then stayed there until the Great Recession came and leapt to 33%, after which it declined back to 25% in late 2011. As the data set includes the lender that originated each loan, we can identify the largest lenders and analyze linear concentration measures of these subsets. Figure 3 reveals a pattern similar to that seen in the CCI. The market share of the largest lender grew dramatically from 8.7% in 2006Q4 to a peak of 23.1% in 2010Q1, for all originated loans. When we add the contributions of the first and second lenders, the market share grows from 17% to a peak of 41% during the same time period. As illustrated by Figure 3, the joint share of the two leading lenders peaked in 2009Q3 (28.67%) at the same time that the CCI attained its maximum of 0.3187. This suggests that the market share of the top two lenders is the major contributor to credit concentration for the CCI. Interestingly, the increasing share of the top two lenders (12%) matched the declining share of the remaining top ten lenders (12.47%), thus suggesting that the latter lost customers to the top two. Similarly, Lenders 11-50 lost part of their market share (−8.05%) to the lender outside the top 100 (8.09%). However, Lenders 51-100 kept the same market share during the most recent recession. In summary, our results confirm the increasing concentration in mortgage origination mainly due to the growing market share of the top two lenders.

Figure 2 Comprehensive Concentration Index

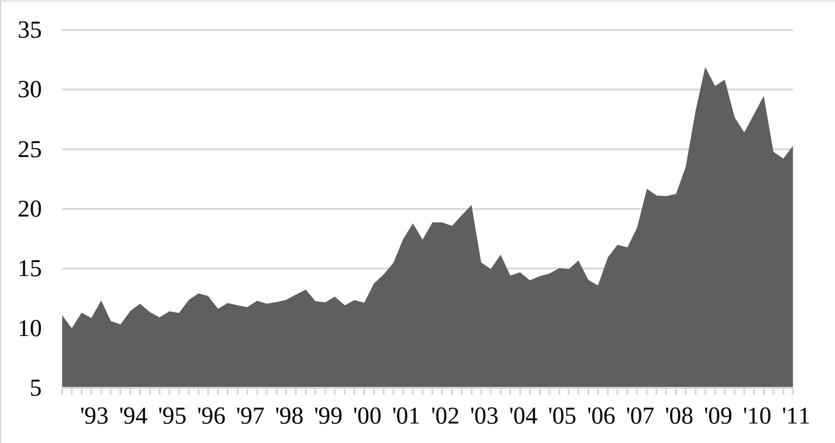
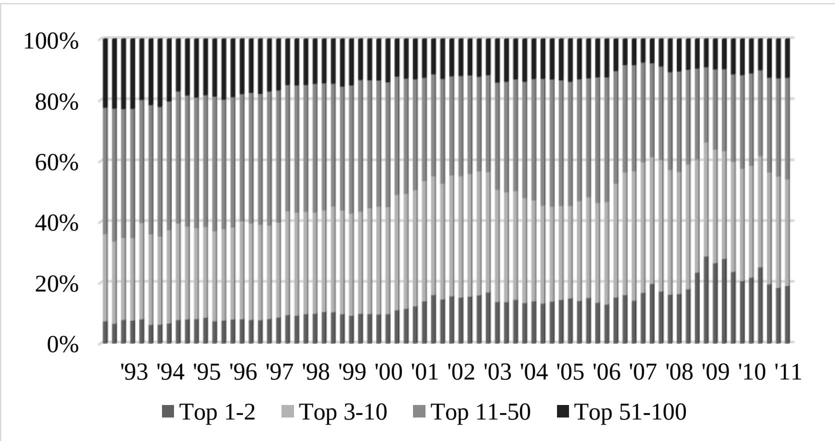


Figure 3 Distribution of Originations by Top 100



3. Lender Concentration and Originator Profits and Unmeasured Costs

3.1 Data for Empirical Study

To examine the impact of the macroeconomic environment on the CCI and the impact of CCI on OPUCs, we incorporate the natural log of real gross domestic product (RGDP) and the Baa-Aaa corporate bond spread in our empirical study. First, OPUCs are obtained and calculated in accordance with Fuster et al. (2013)

and an estimate of profits of lenders net of observable costs. Thus, we consider it a good proxy for the profit of the lenders who are making loans in our dataset. Fuster et al. (2013) define OPUCs as the excess money per $100 lent that is received by the loan originator to cover all marginal costs of originating and serving the loan as well as turning a profit. This measure does not count the fixed insurance payments (g-fees) received by the government-sponsored enterprises (GSEs)[8] Fannie Mae, Freddie Mac, or Ginnie Mae.

It is important to understand that OPUCs as calculated by Fuster et al. (2013) are derived from market average data and not from results or costs of individual lenders. Fuster et al. (2013) specifically note the following key limitations; first, it is based 30-year conventional fixed-rate mortgages and may not be useful for other types of loans; second, because of the aforementioned use of market average data, they can only be used to discuss the industry and not individual lenders; and third, the measure should be viewed as the lower bound of the potential OPUCs of a real lender and thus that of the industry as it cannot measure the various ways that the lender(s) can and sometimes do profit from the securitization process and other profit centers.

Another issue to discuss is the explicit inability to segregate OPUCs into its two component pieces, originators profit (the variable of ultimate interest) and unmeasured costs. It could be rationally asked if the post-recession rise is all attributable to the unmeasured costs (such as those brought upon by increased regulatory burden) and not originators profit. Fuster et al. (2013) actually address this question directly with several empirical tests. They specifically examine the risk/costs of loan putbacks - the probability and cost of buying back a defaulting loan after sale; mortgage servicing rights values - a component of profit that is specifically under threat due to tougher regulatory standards; pipeline hedging costs – the costs of using swaps and other derivatives to protect themselves from adverse market moves between loan commitment and loan sale; and other loan production expense - a catchall that includes direct expenses of loan underwriting and potentially regulatory burdens. In all, Fuster et al. (2013) show empirically that these items *could not* substantially explain the observed rise in OPUCs. Our study is a direct test of one the potential explanations left open by Fuster et al. (2013).

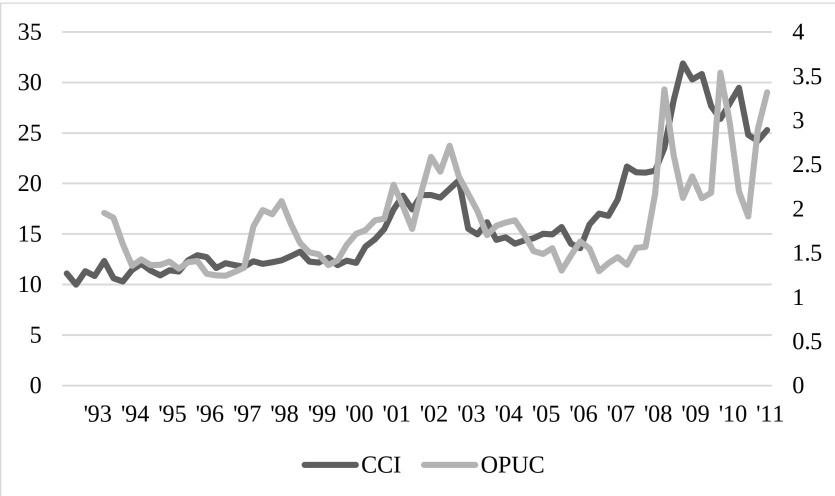
The Spread variable is the difference between the average yield on Baa and Aaa corporate bonds, as rated by Moody’s. Aaa bonds have the highest rating assigned by Moody’s and possess only minimal credit risk, while Baa bonds possess moderate credit risk. Thus, the spread between their yields is a proxy for the risk associated with credit default. A larger or wider Spread indicates that the overall risk of credit default is larger in the current market, while a smaller or narrower Spread indicates less risk. This measure of Spread is believed to move with aggregate market risk assessments of credit default risk,

[8] Details of methodology of Fuster et al. (2013) for calculating OPUCs is presented in the appendix

and thus may rationally impact mortgage rates and the profits of lending institutions.

Figure 4 plots the CCI and OPUCs during the sample period. The figure visually confirms our intuition that the CCI and OPUCs significantly increased during the Great Recession. Additionally, over the entire time series, the Spread has a mean value of 0.958%, with a standard error of 0.456. However, this measure jumps significantly to peak at 3.38% (the minimum was 0.55%) at the height of the Great Recession, thus indicating a large increase in credit default risk. OPUCs spike and display more volatility during the recession, which is also consistent with our hypotheses. Over the entire time series, OPUCs have a mean of 1.848, standard error of 0.527, maximum of 3.538%, and minimum of 1.242%. Finally, the CCI also achieves its highest levels during the Great Recession, consistent with our prediction; this measure has a mean of 16.42 and standard error of 5.73 over the whole time series.

Figure 4 CCI and OPUCs



3.2 Methodology

To test Hypothesis II, we employ unrestricted vector autoregression (VAR) models with the following representation:

$$X = [RGDP, Spread, OPUCs, CCI] \tag{2}$$

where X_t represents a p-element vector (p=4) of n observations on all variables in the system at time t. The VAR model is then specified as follows:

$$X_t = \Gamma_0 + \sum_{i=1}^{k} \Gamma_i X_{t-i} + \varepsilon_t \tag{3}$$

Here, Γ_0 captures the $p\times1$ vector of intercepts, and Γ_i contains the $(p\times p)$ estimated coefficients for each of the k lags (i = 1, 2, ..., k).

As is documented in much of the literature, our data are non-stationary and might have at least one co-integrating relationship. As pointed out by Durlauf and Phillips (1988), Stock (1987), West (1988), and Sims et al. (1990), econometric models can be estimated with raw data in levels if the non-stationary data are also co-integrated. In this case, the ordinary least squares (OLS) (and thus VAR) models provide consistent parameter estimates for non-stationary variables that are co-integrated. Fuller (1976) shows that taking the difference of the dataset in the VAR framework does not lead to any gain in asymptotic efficiency, and might even exclude some relevant information. Thus, all variables used in this study are expressed in natural log rather than in first difference of the natural log.

The choice of the number of lags involves a tradeoff between model parsimony and removing possible biases. That is, using more lags increases the number of parameters which must be estimated, while decreasing the number of lags increases the likelihood of introducing a bias due to omitted variables. We therefore run a test to choose the number of lags k. We employ the likelihood ratio test:

$$(n-c)(\log|\Sigma_r|-\log|\Sigma_u|) \tag{4}$$

where Σ_r and Σ_u are the covariance matrices of the residual series from the restricted and unrestricted systems of equations respectively. Table 1 shows the outcomes of several likelihood tests that compare a possible lag number k to the alternative k–1, along with their chi-squared values and significance levels. The table indicates that the statistically significant lags for Model I are 1, 2, 3, 4, 7, and 11, and for Model II, these lags are 1, 2, and 3. We choose a middle ground, and select four lags for Models I and II.

Next, we employ the impulse response function (IRF) and variance decomposition (VDC) methods to assess whether shocks in the Real Gross Domestic Product (RGDP) can explain movements in the CCI and whether the CCI can explain movements in OPUCs. IRFs show how the dependent variables in a VAR model respond to a one standard deviation shock in the error terms of each independent variable. The VDC test measures the percentage of the forecast error in a given variable that can be explained by its own innovations, as opposed to innovations in the other variables of the VAR model. The IRF indicates the directions of the responses, positive or negative, and whether the responses are statistically significant. The VDC measures the relative importance of each shock on the variables in the VAR. In order to extract these shocks, we consider four different Wold-orderings for X_t:

$$\begin{array}{ll} \text{Specification I:} & X=[RGDP,Spread,OPUCs,CCI] \\ \text{Specification II:} & X=[Spread,RGDP,OPUCs,CCI] \\ \text{Specification III:} & X=[RGDP,Spread,CCI,OPCUs] \\ \text{Specification IV:} & X=[Spread,RGDP,OPUCs,CCI] \end{array} \tag{5}$$

Table 1 Tests for lag length

	Model I	Model II
12 versus 11 lags	30.9330 (0.0137)**	20.0333 (0.2187)
11 versus 10 lags	17.7332 (0.3398)	7.1514 (0.9702)
10 versus 9 lags	12.5099 (0.7082)	16.5387 (0.4160)
9 versus 8 lags	12.9740 (0.6747)	16.5387 (0.4160)
8 versus 7 lags	20.5277 (0.1974)	20.6766 (0.1913)
7 versus 6 lags	25.5427 (0.0608)*	17.5237 (0.3525)
6 versus 5 lags	15.0961 (0.5176)	14.2336 (0.5813)
5 versus 4 lags	21.4804 (0.1608)	11.9897 (0.7447)
4 versus 3 lags	34.7753 (0.0043)***	18.3397 (0.3044)
3 versus 2 lags	32.6716 (0.0082)***	25.3426 (0.0640)*
2 versus 1 lags	56.8458 (0.0000)***	65.4046 (0.0000)***
2 versus 1 lags	13412 (0.0000)***	13671 (0.0000)***

Notes: This table reports the likelihood ratio test for the determination of the lag length (K). The table reports the chi-squared statistics and their significance level. Note: ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels respectively.

Furthermore, we stipulate the following relationship between the reduced form errors, ε_t, and the underlying structural shocks, μ_t:

$$\mu_t = C\varepsilon_t \tag{6}$$

where C is a lower triangular matrix and ε_t has a covariance matrix equal to the identity matrix. Next, we use Cholesky decomposition to obtain the underlying structural relationships and perform innovation accounting.

3.3 Empirical Results

Figures 5 and 6 depict the IRFs of OPUCs and the CCI to innovations in RGDP, Spread, CCI, and OPUCs for the specification I[9]. The figures show the responses of OPUCs and CCI to a one standard deviation shock in the RGDP, Spread, and OPUCs and the 90% confidence intervals of the responses over a sixteen-quarter horizon.

Figure 5 shows the impulse responses of the OPUCs. Interestingly, a one standard deviation shock in the CCI had a positive effect on OPUCs, as suggested by Hypothesis II. The impact was statistically significant during quarters 5, 8, 9, and 11, and the accumulated significant response averaged 0.39 over the four specifications. The graph also reveals that OPUCs increased for two quarters following its own shock. A shock in the Spread significantly and positively affected OPUCs during the first two quarters. Finally, a shock in the RGDP had a negative effect on OPUCs. The impact was statistically significant during quarters 3 and 4 in the four specifications.

Figure 6 reveals that the CCI responded negatively and significantly during quarters 4, 5, and 6 to a one standard deviation shock in the RGDP, in all four specifications. In addition, a shock in the CCI had a positive and significant effect on the CCI for almost nine quarters. Finally, the CCI did not generally respond significantly to shocks in the spread or in the profits of the lenders. These two variables jointly account for less than 8% of the variance in the CCI during the sixteen-quarter horizon.

Figures 7 and 8 illustrate the VDC of OPUCs and the CCI for the four specifications. Interestingly, the overall patterns are identical across the four specifications. Figures 7 and 8 reveal that OPUCs account for 81% of their own variance during the first two quarters, and 48% of their own variance during the remaining fourteen quarters. RGDP, CCI, and Spread account for 18%, 21%, and 12% of the variance in OPUCs respectively during quarters 3 to 16. A shock in the CCI accounts for about 86% of its own variance during the first year, and about 55% during the remaining three years. RGDP, OPUCs, and Spread account for 23%, 17%, and 6% of the remaining variance respectively during quarters 3 to 16.

In sum, our IRFs confirm the existence of a negative relationship between the RGDP and both OPUCs and the CCI, while a positive relationship exists between the CCI and OPUCs as predicted by Hypotheses I and II. The RGDP explains for about 18% and 23% of the variance in the forecast errors of OPUCs and the CCI respectively after early quarters, once the variables had time to interact with each other. In addition, the increased lending concentration contributed to higher lender profits (OPUCs), and accounted for 21% of the

[9] It should be noted that the following results of Specification I are stable under the three alternative Wold-orderings.

variance in the forecast error during quarters 1 and 2. It should also be noted that increased credit concentration is associated with a significant decrease in the total amount of loans originated by the top ten originators. For example, the average amount of loans originated by the top two lenders between 2007:03 and 2009:02 dropped by $6,819,303,251 relative to the average amount of loans offered by the top two lenders between 2006:01 and 2007:02, despite the fact that their market share increased from 14% to 23% over the same period. Thus, the increased concentration and OPUCs cannot be attributed to economies of scale. Finally, to show the economic significance of the increased CCI during the recession on OPUCs and thus potentially costs to the borrower, an estimate is derived by using the parameters from the empirical analyses. The size of one standard deviation in the CCI was .72 for the period between 1993:01 and 2011:04. The impulse responses show that a shock of one standard deviation in the CCI caused the OPUCs to increase by 0.39 during the four years following the shock. For the period between 2007:01 and 2011:01, the CCI increased by 13.53 or 2.365 standard deviations. As a result, the OPUCs increased by 0.93 percent, meaning that borrowers faced up to a 93 basis point increase in their interest rate and/or loan fees. This calculation, based on the impulse response of OPUCs to a one standard deviation shock in the CCI depicted in Figure 9, is detailed in Table 2.

Table 2 Calculation of Change in OPUCs given Rise in CCI

	CCI	OPUCs
Size of one standard deviation	5.72	
A shock of 1 standard deviation in CCI increases OPUCs by 0.3947	1	0.3947
Change in CCI for the period between 1994 and 2011	1.35	
Change in CCI in terms of standard deviation = 0.125/.0572	2.36	
A shock of 2.36 standard deviations increases OPUCs by (0.784 x 2.36)		0.93%

Note: Derived from the sum of the statistically significant responses of OPUCs to a one standard deviation shock in CCI for all four specifications, the average of the significant responses is 0.39. The responses used for calculation are restricted to the statistically significant ones where the zero line is not located between the upper and lower 90% confidence intervals

Figure 5 Impulse Responses of OPUCs

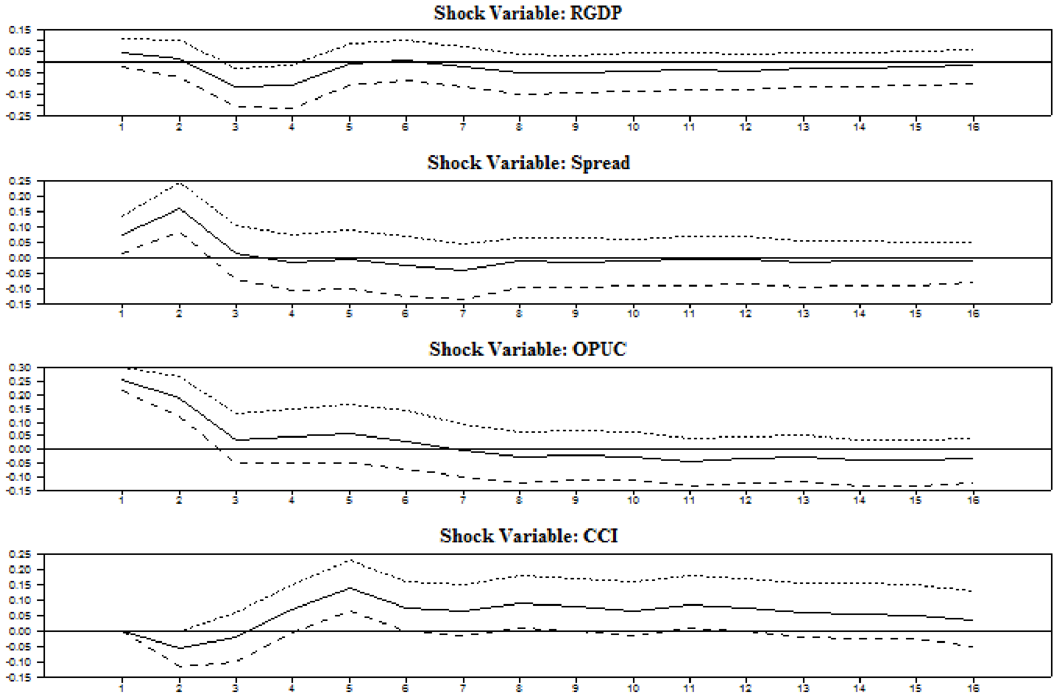


Figure 6 Impulse Responses of CCI

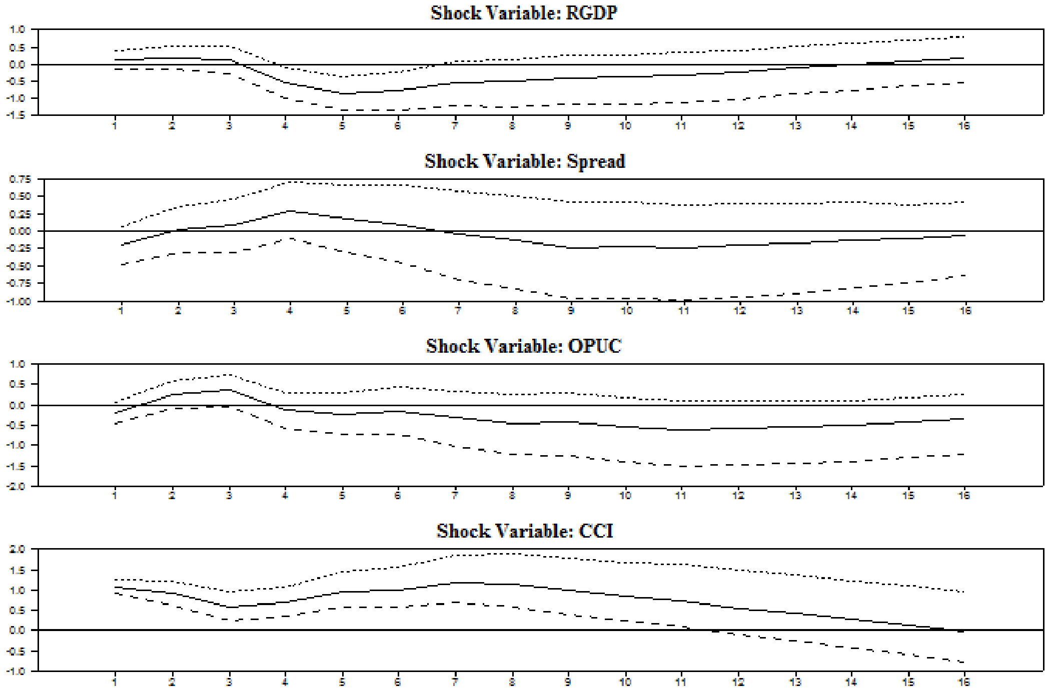


Figure 7 Variance Decomposition of OPUCs

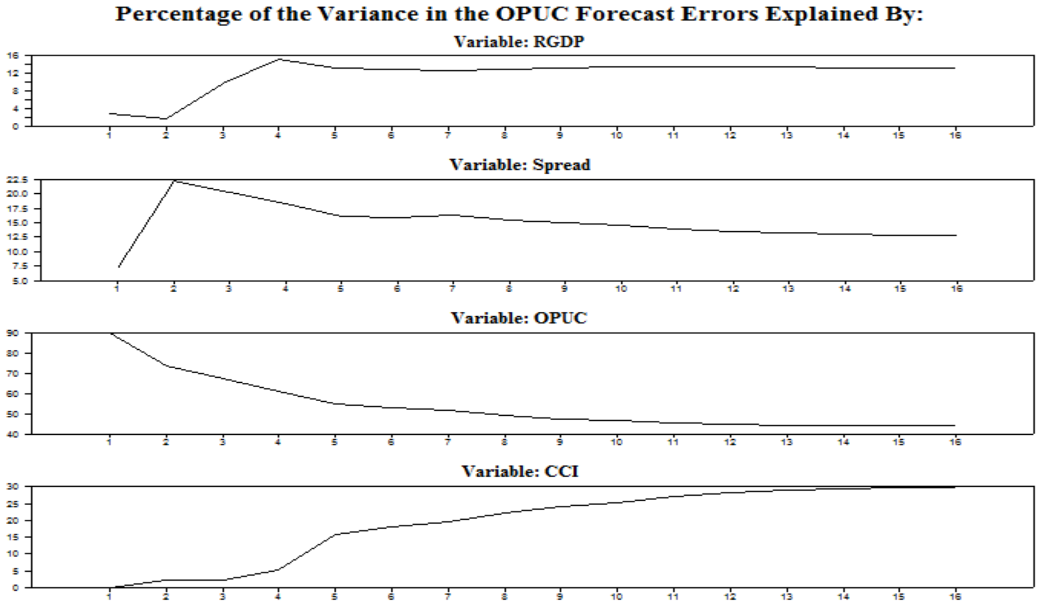


Figure 8 Variance Decomposition of CCI

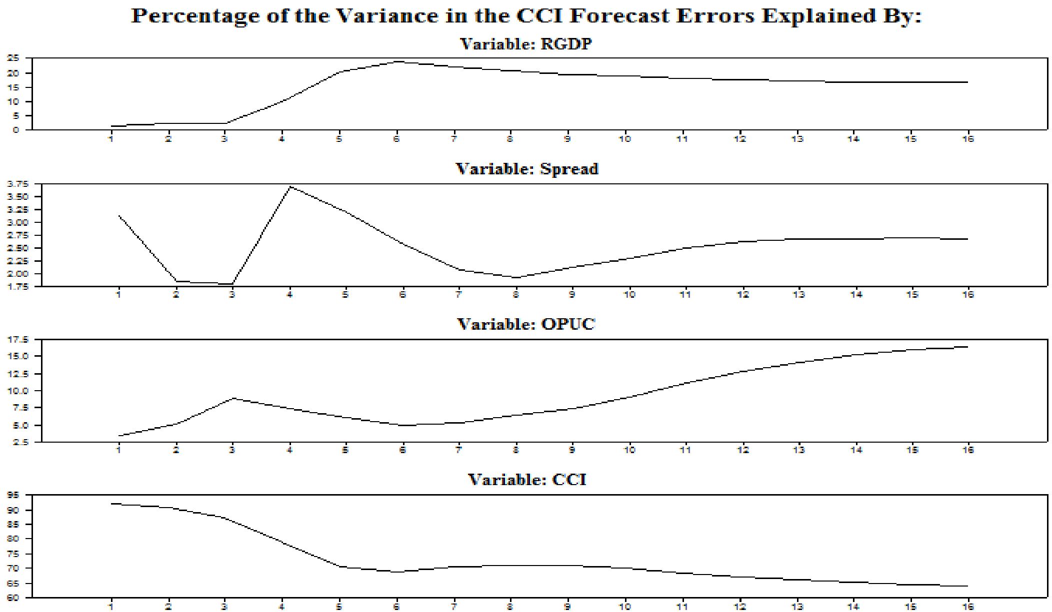
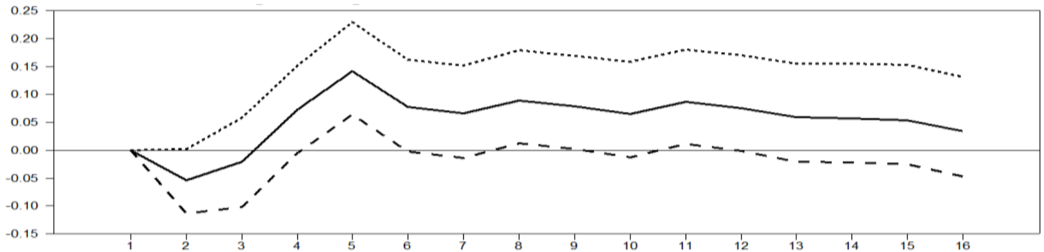


Figure 9 Impulse Responses of OPUCs to a One Standard Deviation Shock in CCI



4. Conclusion

We empirically examine whether mortgage costs, as proxied by OPUCs, increase as a result of rising concentration of the largest 100 originators, as measured by the CCI over the period of 1993 to 2011. We find that OPUCs did indeed increase with an increasing CCI and that borrowers were most likely worse off as lenders consolidated and became larger, as they could exert more monopolistic power. As such, it is rational to deduce that borrower ability to shop for loans and the competitive nature of the mortgage market do in fact partially determine rates and fees charged by lenders and thus their profit, irrespective of pure credit risk determinations of the borrower and loan. Much of the literature on mortgage lending have focused on the borrower and loan as the unit of concern, with limited tests or controls for competitiveness of the mortgage market. We believe the results herein strongly suggest that the degree of competitiveness in the mortgage market may be partially deterministic in the fees and costs that borrowers face; as such, more "competition" variables and controls should be used in future research.

Further to this issue, we find that economic conditions appear to influence the concentration of originations. We find that during the 2001 recession, mortgage originations became more concentrated in a few large institutions. The credit concentration started at 10% in 1993 (a year of economic recovery), and increased to 15% by the end of the 2001 recession. Another major increase came in 2009, when the CCI jumped to 30% and the single largest lender was providing 23% of the total dollar amount of all loan originations from the top 100 lenders. At that time, the top two lenders provided over 40% of all loan originations by the top 100 lenders, and more than 26% of all loans offered by the entire financial sector. This finding serves as empirical proof to the propositions of Calem and Follain (2007). This increase in OPUCs raises the concern that financial institutions may have exerted monopolistic power to gain higher profits than justified by market conditions. Empirically, we estimate this increase in originator profits and unobserved profits to be 0.93% from 2007 to 2011, a very economically significant amount. This appears to be above what is required for proper risk control given control measures used and discussed herein; however, it is not necessarily our view that lenders may be acting as monopolists when setting fees and charges. Igan and Pinherio (2010) show that a 1.3 percentage point increase in mortgage interest rate can lead up to a 20% reduction in the bank's overall default risk; thus, the rising OPUCs may be as a result of the issues embedded in the lending institution, not the borrowers or loan credit quality. This interpretation is consistent with Calem and Follain (2007). Nonetheless, the originating lending institutions keep the benefits of higher profits and portfolio risk protection so long as they do not subsequently default; these benefits are of course paid for by the borrower.

Additionally, our findings suggest that lenders are rationally motivated to become large and control larger shares of the mortgage market to maximize profitability. While large metropolitan markets may always have a vast array of lending institutions to choose from, smaller and rural markets may suffer disproportionally from consolidation. Even more troubling, lenders may choose to enter a market or acquire competitors based on their expectations of gaining monopolistic power on a regional basis. Further research is needed to determine if geographic concentration also impacts the profits of lenders. If confirmed, this effect again could have significant policy implications.

Finally, it worth noting some of the limitations of this study, which could be explored in future research. First, the degree to which consumers have the ability to “shop” for home loans is not measurable in our dataset. The ability of consumers to compare loans from multiple banks and other lending sources (which can be done online and via the telephone) could impact the monopolistic power of lenders and thus their ability to earn higher profits. Second, we do not attempt to measure the impact of secondary market activity for mortgage loans. This market exists outside of the consumer’s initial choice for a loan originator, but can absolutely impact the pricing and availability of new loans offered by lenders. Subsequent studies should attempt to merge the literature on secondary mortgage markets with that on credit concentration in the primary market. For example, Scharfstein and Sunderam (2013) suggest that increases in lending concentration can reduce the impact that a drop in mortgage-backed security yields have on the primary lending market. This finding further supports our conclusions, and highlights the need to investigate secondary market effects as moderators and amplifiers of lending concentration on the profits of originators.

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Appendix

OPUC Calculations

Empirically, Fuster et al. (2013) calculate OPUCs as the sum of two components:

I. The *origination cash flow* is the difference between (1) the cash received by the loan originator, that is, the price paid by the borrower for a securitized mortgage loan of $100 in the secondary market; and (2) the cash paid by the originator, meaning the $100 given to the borrower and the up-front insurance premium paid to a GSE.

II. The present value of all future cash flows generated by servicing the loan.

To construct the time series of the OPUCs, Fuster et al. (2013) take the following steps:

A. Construct a hypothetical mortgage loan based on the weekly survey rate and average points paid from Freddie Mac's Primary Mortgage Market Survey.

B. Construct the g-fee by assuming that the loan-level price adjustments received by the GSEs are paid over the life of the loan.

C. Use fixed multiples of 5x, 4x, and 7x to calculate base servicing (obligations to service the loan, such as collecting payments from borrowers), excess servicing (servicing income in excess of 25 basis points), and buy-downs respectively.