14.03/003 Microeconomic Theory & Public Policy, Fall 2022

Lecture 21. Moral Hazard and Subprime Lending

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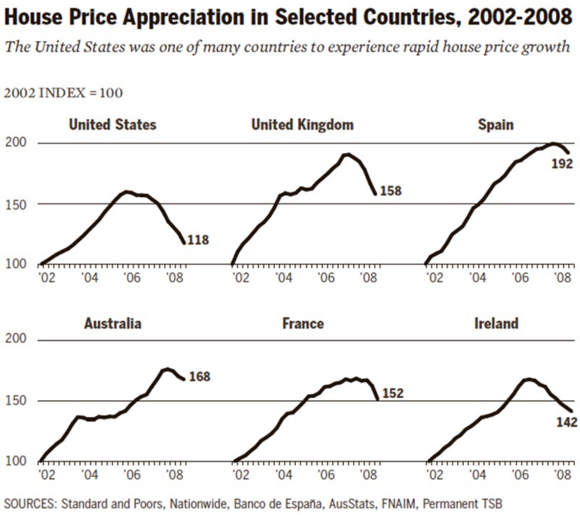
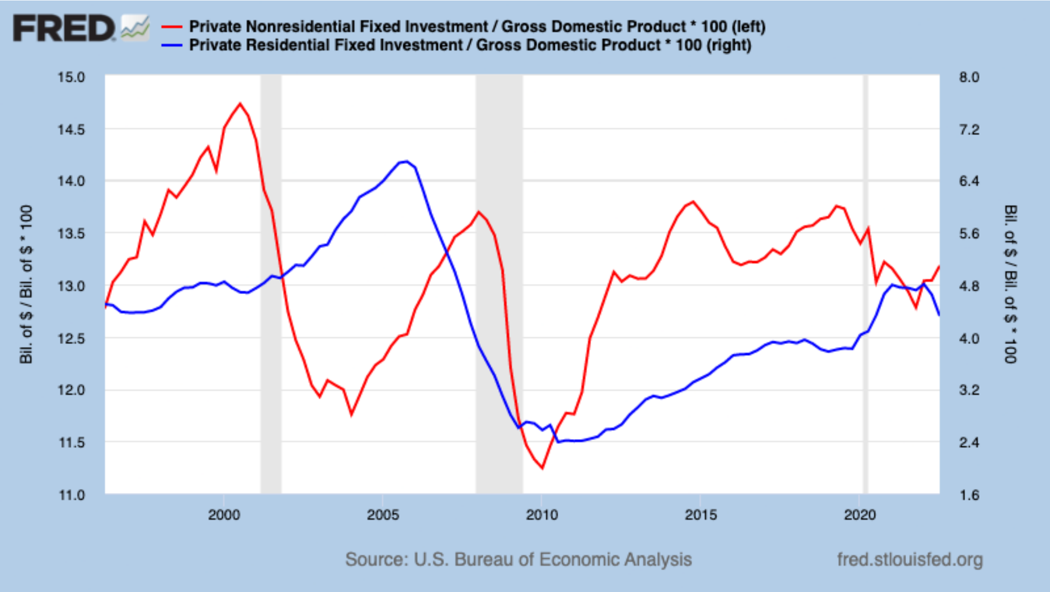
Worldwide Real Estate Bubbles, 2002 – 2008



U.S. Residential Investment Surged Between 2002 and 2007



Did Securitization Lead to Lax Screening? Evidence From Subprime Loans

Keys et al. (2010)

Background: Securitization

Definition: A mortgage-backed security (MBS) is a type of asset-backed security which is secured by a mortgage or collection of mortgages. (*Wikipedia*)

- One asset is "backed" by many borrowers (risk pooling).
- Works essentially like a bond where the buyer of the asset receives a stream of interest payments.
- The idea behind MBS was to spread risk over many asset holders.
- Holder of asset faces the risk that borrowers default.
- During the financial crisis this default risk became an aggregate risk.

Freddie Mac Guidelines for Prime vs. Subprime Lending

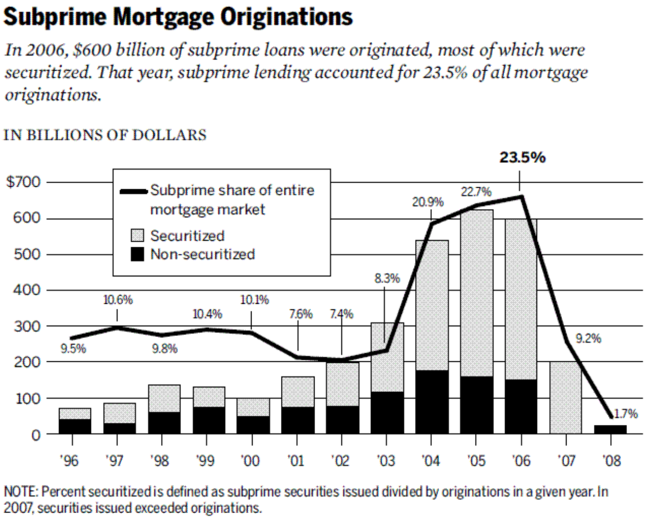
While not the only ingredient in market estimates of credit quality, FICO scores (credit scores developed by Fair Isaac and Company) provide a useful measure for quantifying default risk. In general, first-trust mortgage borrowers with FICO scores above 660 are considered to have a good credit reputation. ***Borrowers with FICO scores between 660 and 620 are somewhat riskier borrowers, for whom underwriters should perform a more extensive review. Borrowers with scores below 620 should be subjected to a thorough, cautious review.***

Key Idea

Mortgage issuers gather both **hard** and **soft** information on borrowers. An industry rule of thumb "allowed" loans above a FICO score of 620 to be securitized.

- Loans above 620 can get securitized, loans below 620 are harder to securitize and sell.
- If the additional risk is not properly priced, banks have an incentive to screen less thoroughly above 620.

Subprime Mortgage Originations, 1992 – 2008



By National Commission on the Causes of the Financial and Economic Crisis in the United States - Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States, p.70 figure 5.2, Public Domain

Distribution of Fair-Isaac Credit Scores in the U.S. in 2004

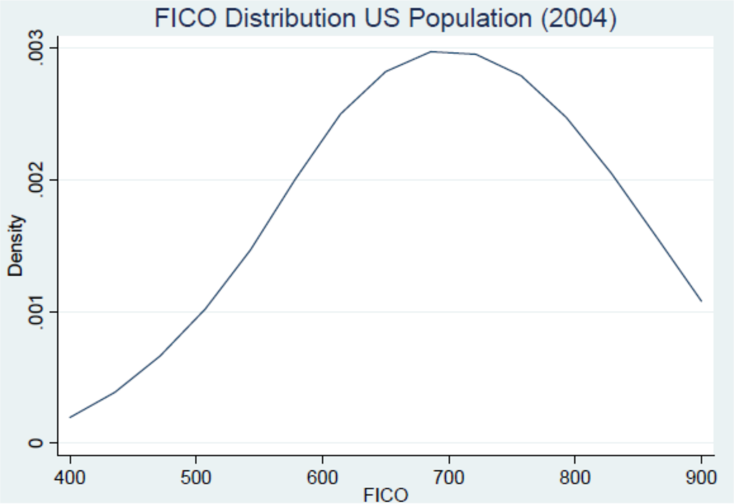


Figure 1: FICO Distribution (US Population)

Figure 1 presents the FICO distribution in the U.S. population for 2004. This data is from an anonymous credit bureau which assures us that the data exhibits similar patterns during the other years of our sample. The FICO distribution across the population is smooth, so the number of prospective borrowers in the local vicinity of a given credit score is similar.

Number of Loans by FICO Score: Low-Documentation Loans

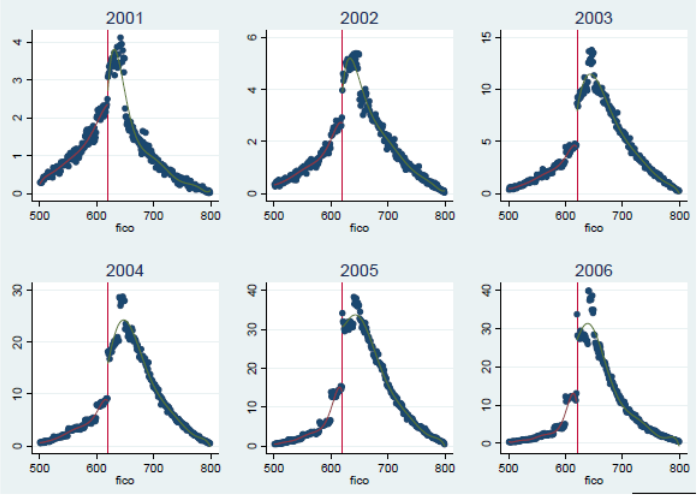


Figure 2: Number of Loans (Low Documentation)

Figure 2 presents the data for number of low documentation loans (in '00s). We plot the average number of loans at each FICO score between 500 and 800. As can be seen from the graphs, there is a large increase in the number of loans around the 620 credit threshold (i.e., more loans at 620^{+} as compared to 620^{-}) from 2001 onwards. Data is for the period 2001 to 2006.

Quick Review:
Regression Discontinuity Design

Regression Discontinuity Design

- For each individual i: Y_{i1} for what would occur if the unit were exposed to the treatment and Y_{i0} if not exposed.
- The causal effect of the treatment is represented by the difference $T = Y_{i1} - Y_{i0}$.
- As usual, the fundamental problem of causal inference is that we cannot observe the pair Y_{i1} and Y_{i0}.
- We have typically handled this problem through:
  - Explicit **experimental randomization** (tax salience experiment)
  - **Difference-in-difference** estimation (NJ minimum wage increase)
  - **Instrumental variables** (air-sea differential distance)

Regression Discontinuity Design

- All of these methods attempt to find units that are in expectation comparable—that is, their potential outcomes if treated (or if untreated) do not differ in expectation.
- The Regression Discontinuity (RD) estimator takes a novel approach to identifying a causal relationship when the treatment and control groups do *not* have potential outcomes that are identical in expectation.
- It instead looks for units that are *arbitrarily close* in terms of their potential outcomes and yet are treated differently (one assigned to treatment, the other assigned to control) due to some bright line rule used to assign them.

Examples

- A national election can be decided by a single vote
- The cutoff for majoring in Economics at UC Santa Cruz is 2.8

Regression Discontinuity Design

Why are such **arbitrary cutoffs** useful?

- Define a variable X that is used to determine the cutoff.
- Imagine there are two underlying relationships between potential outcomes and X, represented by $E[Y_{i1}|X_i]$ and $E[Y_{i0}|X_i]$.
- And let's say that individuals to the right of some cutoff c (let's say $X_i \geq 0.5$) are exposed to treatment, and all those to the left $(X_i < 0.5)$ are denied treatment.
- Therefore, we only observe $E\left[Y_{i1}|X_i\right]$ to the right of the cutoff and $E\left[Y_{i0}|X_i\right]$ to the left of the cutoff.

As we consider units i that are **arbitrarily close** to the threshold, it would be reasonable to assume that:

$$
\begin{aligned}
\lim_{\varepsilon \downarrow 0} E\left[Y_{i1}|X_i = c + \varepsilon\right] &= \lim_{\varepsilon \uparrow 0} E\left[Y_{i1}|X_i = c + \varepsilon\right], \\
\lim_{\varepsilon \downarrow 0} E\left[Y_{i0}|X_i = c + \varepsilon\right] &= \lim_{\varepsilon \uparrow 0} E\left[Y_{i0}|X_i = c + \varepsilon\right].
\end{aligned}
$$

Regression Discontinuity Design

That is, for units that are *almost identical*, we can say that if they had both been treated (or not treated), their outcomes would have been **arbitrarily similar**.

If so, then we can form a Regression Discontinuity estimate of the causal effect of treatment on outcome Y using the contrast:

$$\hat{T} = \lim_{\varepsilon \downarrow 0} E\left[Y_i | X_i = c + \varepsilon\right] - \lim_{\varepsilon \uparrow 0} E\left[Y_i | X_i = c + \varepsilon\right],$$

which in the limit is equal to:

$$T = E\left[Y_{i1} - Y_{i0} | X_i = c\right].$$

This is the key idea underlying the RD technique used for causal inference by Keys et al.

Number of Loans by FICO Score: Low-Documentation Loans

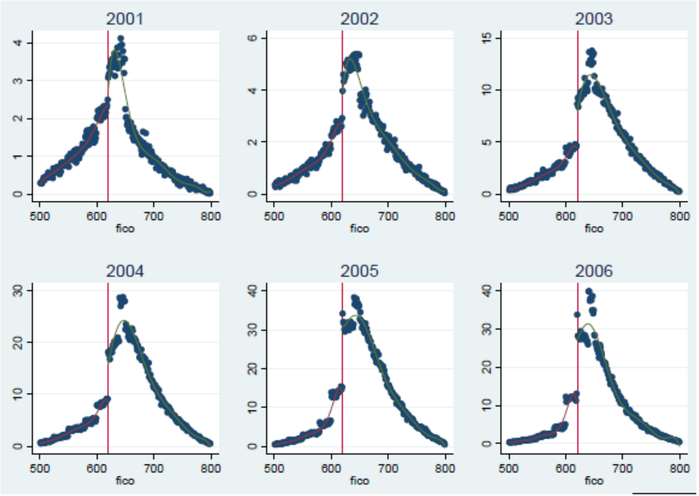


Figure 2: Number of Loans (Low Documentation)

Figure 2 presents the data for number of low documentation loans (in '00s). We plot the average number of loans at each FICO score between 500 and 800. As can be seen from the graphs, there is a large increase in the number of loans around the 620 credit threshold (i.e., more loans at 620^{+} as compared to 620^{-}) from 2001 onwards. Data is for the period 2001 to 2006.

Surge in 'Low-Documentation' Loans Starting in 2003

TABLE I

Summary Statistics

Panel A: Summary statistics by year

	Low documentation			Full documentation		
	Number of loans	Mean loan-to-value	Mean FICO	Number of loans	Mean loan-to-value	Mean FICO
2001	35,427	81.4	630	101,056	85.7	604
2002	53,275	83.9	646	109,226	86.4	613
2003	124,039	85.2	657	194,827	88.1	624
2004	249,298	86.0	658	361,455	87.0	626
2005	344,308	85.5	659	449,417	86.9	623
2006	270,751	86.3	655	344,069	87.5	621

Interest Rates: Low-Documentation Loans

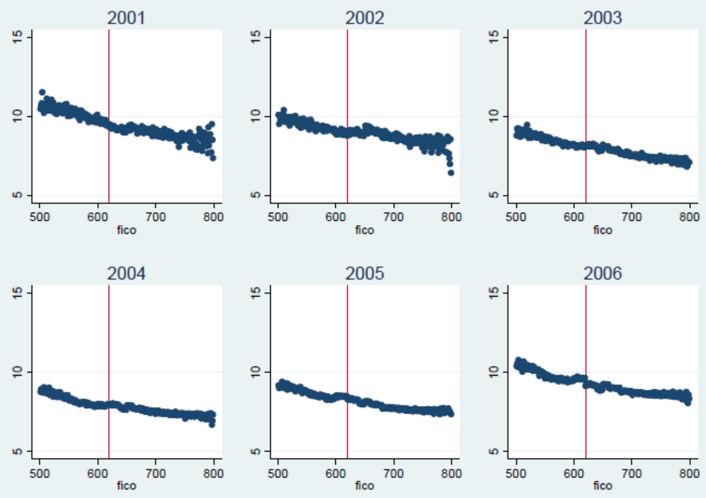


Figure 3: Interest Rates (Low Documentation)

Figure 3 presents the data for interest rate (in %) on low documentation loans. We plot average interest rates on loans at each FICO score between 500 and 800. As can be seen from the graphs, there is no change in interest rates around the 620 credit threshold (i.e., more loans at 620^{+} as compared to 620^{-}) from 2001 onwards. Data is for the period 2001 to 2006.

Median Household Income: Low-Doc Loans

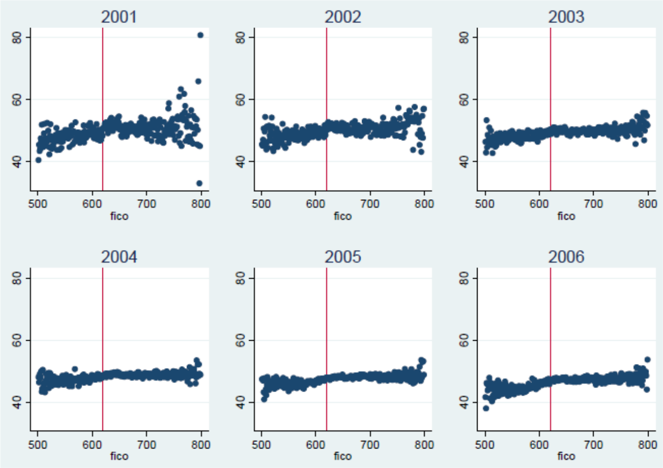


Figure 5: Median Household Income (Low Documentation)

Figure 5 presents median household income (in '000s) of zip codes in which loans are made at each FICO score between 500 and 800. As can be seen from the graphs, there is no change in median household income around the 620 credit threshold (i.e., more loans at 620^{+} as compared to 620^{-}) from 2001 onwards. We plotted similar distributions for average percent minorities taking loans, and average house size and find no differences around the credit thresholds. Data is for the period 2001 to 2006.

Loan-to-Value Ratio: Low-Documentation Loans

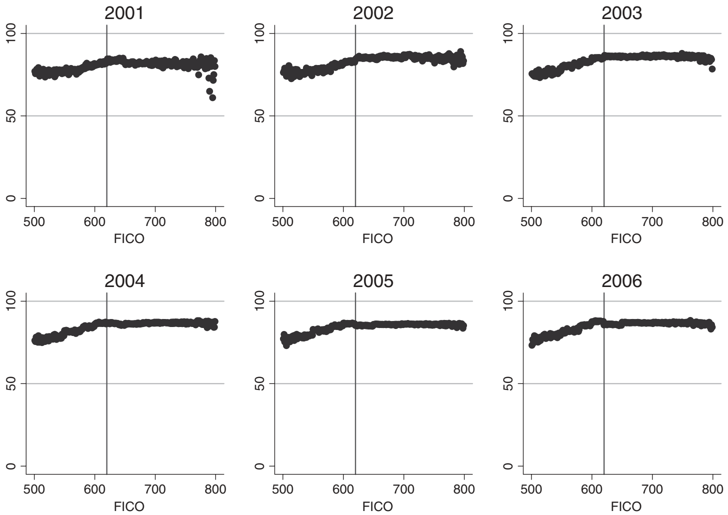


FIGURE IV
Loan-to-Value Ratio (Low-Documentation)

Annual Delinquencies in 2001: Low-Doc Loans

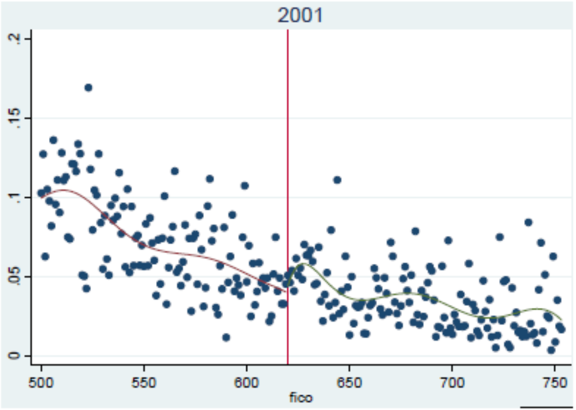


Figure 6A: Annual Delinquencies for Low Documentation Loans in 2001

Figure 6A presents the percent of low documentation loans that became delinquent in 2001. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

Annual Delinquencies in 2002: Low-Doc Loans

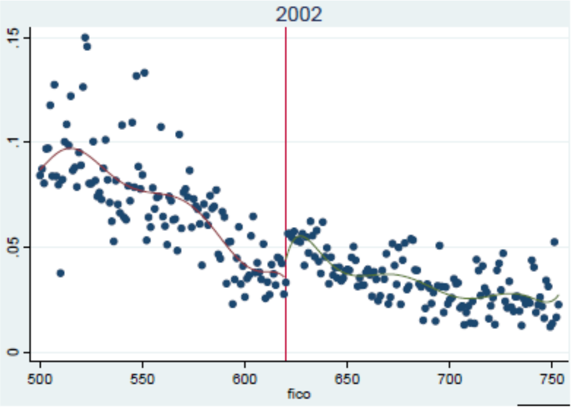


Figure 6B: Annual Delinquencies for Low Documentation Loans in 2002

Figure 6B presents the percent of low documentation loans that became delinquent in 2002. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

Annual Delinquencies in 2003: Low-Doc Loans

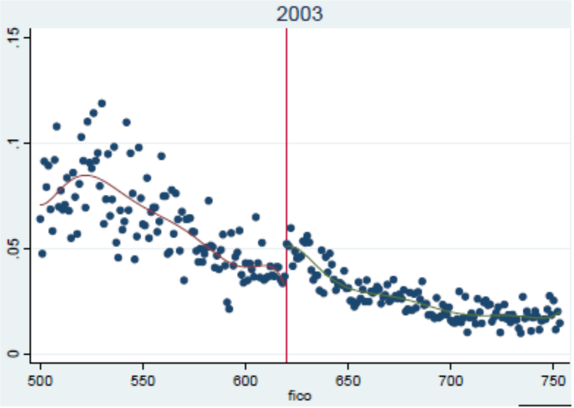


Figure 6C: Annual Delinquencies for Low Documentation Loans in 2003

Figure 6C presents the percent of low documentation loans that became delinquent in 2003. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

Annual Delinquencies in 2006: Low-Doc Loans

Figure 6F: Annual Delinquencies for Low Documentation Loans in 2006

Figure 6F presents the percent of low documentation loans that became delinquent in 2006. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

Annual Delinquencies: *Full-Documentation Loans*

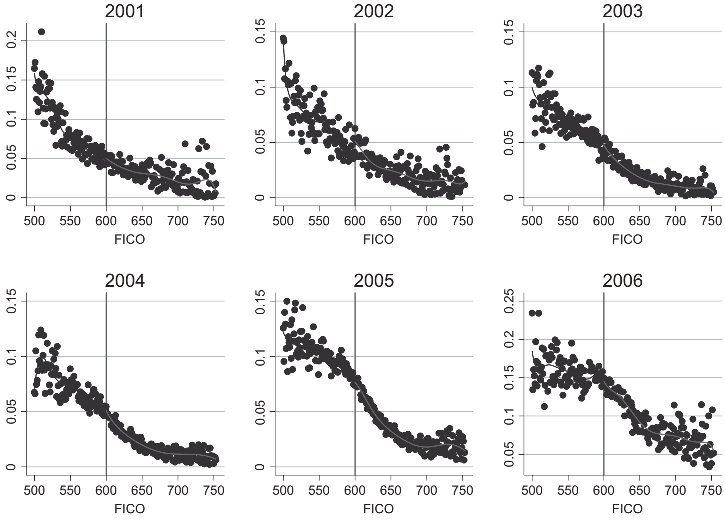


FIGURE XII
Annual Delinquencies for Full-Documentation Loans

Cumulative Delinquencies 2001 – '06: Low-Doc Loans

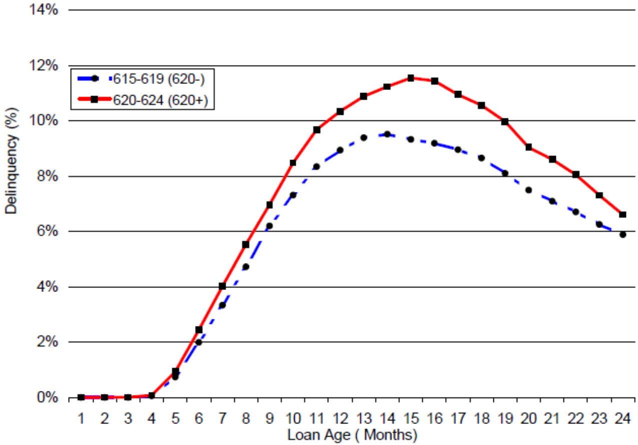


Figure 7: Delinquencies for Low Documentation Loans (2001-2006)

Figure 7 presents the percent of low documentation loans (dollar weighted) that became delinquent for 2001 to 2006. We track loans in two FICO buckets – 615-619 (620^-) in dotted blue and 620-624 (620^+) in red – from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *more* than the lower credit score bucket for post 2000 period. For brevity, we do not report plots separately for each year. The effects shown here in the pooled 2001-2006 plot are apparent in every year.

Cumulative Delinquencies 2001 – '06: Full-Doc Loans

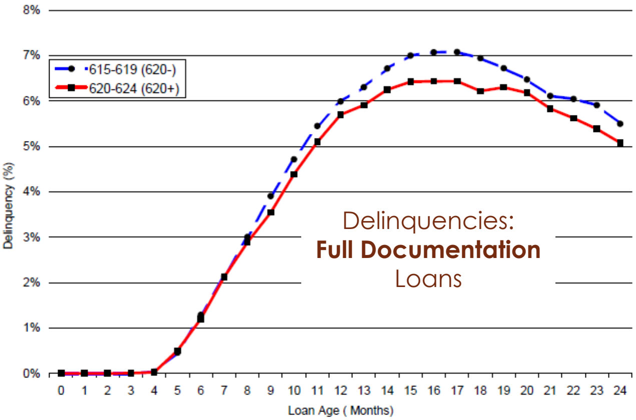


Figure 10: Falsification Test - Delinquencies for Full Documentation Loans Around FICO of 620

Figure 10 presents the falsification test by examining the percent of full documentation loans (dollar weighted) that became delinquent for 2001 to 2006. We track loans in two FICO buckets – 615-619 (620^-) in dotted blue and 620-624 (620^+) in red – from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *less* than the lower credit score bucket for post 2000 period. For brevity, we do not report plots separately for each year. The effects shown here in the pooled 2001-2006 plot show up for every year.

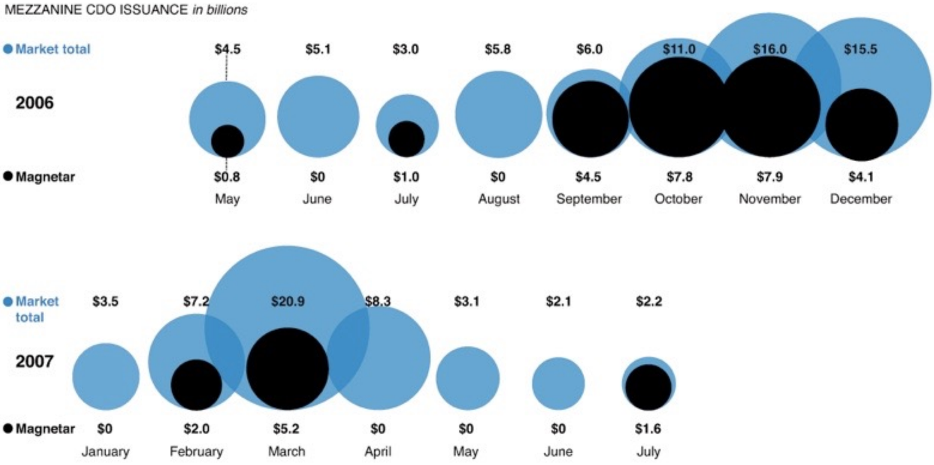
Highly recommended podcast:

"Inside Job" *This American Life*, April 2020

Collateralized Debt Obligation

- A financial product structured by banks that pools and packages cash-generating assets into financial securities, which are then sold to investors.
- A mortgage-backed security is one form of a CDO, where mortgages are the collateral.
- Investors expect to profit from the repayment of mortgage loans. Investment returns fall—and can become substantially negative—if the default rate of mortgages in the CDO proves higher than expected.

Magnetar's Involvement in CDO Issuance in 2006-'07: Black Bubbles Equal Magnetar's Share of CDO Issuance



Sources: PF2 Securities Evaluations Inc., S&P, ProPublica

Synthetic Collateralized Debt Obligation (CDO)

- **CDOs are typically divided into three tranches w/different risk/return profiles**

    1. **Senior** tranche includes securities with high credit ratings, tends to be low risk, and thus has lower returns. This tranche pays positive returns unless a very large share of loans defaults.
    2. **Mezzanine** tranche has somewhat higher risk and somewhat higher expected return. It pays positive returns unless a moderately high share of loans defaults.
    3. **Equity** tranche offers high expected returns. But default risk is concentrated in this tranche — that is how other tranches are shielded. It's the shock absorber for the other two tranches.

The Magnetar Trade: How One Hedge Fund Helped Keep the Bubble Going

The hedge fund helped create mortgage-based securities, pushed for risky things to go inside them and then bet against the investments, resulting in billions in losses for investors and ultimately making the financial crisis worse. It's a story of the perverse incentives and reckless behavior that characterized the last days of the boom.

by Jesse Eisinger and Jake Bernstein • April 9, 2010, 12:59 p.m. EDT