Essays in Real Estate Finance and Behavioral Economics

by

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Committee in charge:

Professor Nancy Wallace, Chair
Professor Amir Kermani
Professor Christopher Palmer
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Abstract

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This dissertation consists of two chapters. The first one deals with the information content of bond prices in private label securitization markets. The performance of a security backed by a pool of loans is affected by default correlation, and not only the probability of default. I imply default correlation from the market price of collateralized mortgage obligations. Implied correlations are informative about subsequent bond downgrades, but this information content depends on the quality of documentation on the underlying loans. Correlations implied from junior tranches are no more informative than those of AAA tranches for "low-doc deals, and the latter no less informative than the former for "full-doc deals. Errors in computing default correlations were not exclusive to AAA investors.

The second chapter in this dissertation deals with the structural estimations of utility-based models in a setting of economic decision-making. Dropping the assumption that all individuals are all self-regarding we develop a model of utility maximization under social preferences. We use data from a common pool resource (CPR) game run in the field (1,095 subjects) to estimate a structural model including preferences for selfishness, altruism, reciprocity and equity, identifying preference types using a latent class logit model. Exogenous determinants of type are examined such as socio-economic characteristics, perceptions on the CPR, perceived interest in cooperation among the community, whether the participant does volunteer work and whether the CPR is the household main economic activity of the household. A competing explanation of deviations from Nash equilibrium is the existence of a cognitive factor: the construction of a best reply might make rational expectations about other players mistakes (e.g. quantal response equilibrium). We do not find evidence for cognitive heterogeneity. Choice prediction based on types is robust out of sample.

To Mary, María Cristina and Sandra

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Chapter 1

Information Frictions in Securitization Markets: Investor Sophistication or Asset Opacity?

Because the central premise of securitization is diversification through pooling, default correlations are crucial to bondholders. Hence prices of structured products that are subject to default risk reveal investors' beliefs about correlations. Higher correlations imply more volatility of the portfolio cashflows, which is valuable to subordinate bondholders but detrimental to senior ones (Duffie and Gârleanu, 2001). Yet there is still a lack of attention to default correlations -which Duffie, 2008 deems the "weak link" in the pricing of collateralized debt obligations (CDO)- relative to the attention given to default probabilities.

Coval, Jurek, and Stafford, 2009a[1] show that bond prices are sensitive to underlying default correlations, and that this sensitivity compounds along the structured finance chain. As (Cordell, Huang, and Williams, 2012) show (see Figure 1.0.1) the underlying collateral of cash CDOs is predominantly mezzanine tranches of collateralized mortgage obligations (CMO). This means that in practice CDOs behave -with respect to the underlying loans- the way CDO^2 behave in Coval, Jurek, and Stafford, 2009a. Thus Coval, Jurek, and Stafford, 2009a highlight the importance of CMO default correlations, while leaving the question open as to which investors are miscalculating them.

To calculate impleid correlations I use the pricing model that Hull and White, 2006 call "the standard market model for valuing collateralized debt obligations and similar instruments", namely a single factor Gaussian copula (Li, 2000).[2] I estimate the probability of default (PD) and loss given default (LGD) from loan performance data, following common

[1]Our estimate of default correlation uses the same method as they do. Using their parameters I replicate their results (see Figure 1.3.1).

[2]See also Brunne, 2006; D'Amato and Gyntelberg, 2005; Duffie and Singleton, 2012; Elizalde, 2005; Hull and White, 2004; Hull and White, 2006; Hull and White, 2008; McGinty et al., 2004; Tzani and Polychronakos, 2008.

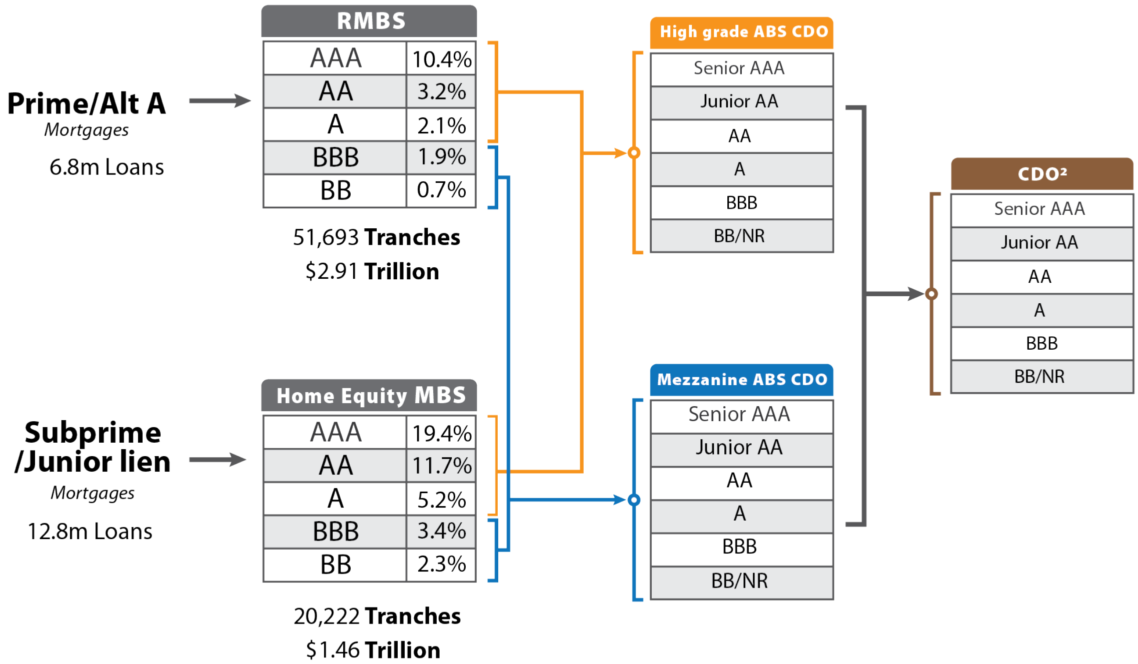


Figure 1.0.1: Diagram: from loans to RMBS CMO, from CMO to CDO, from CDO to CDO^2. Details are reported on the total number of loans recorded by ABSNet, the universe of securities issued and the average subordination percentage by Standard & Poor's rating, as explained in Section 1.2

practice in CDO pricing models that PD and LGD on the underlying asset are taken as given, and correlations are directly implied from market prices of the bonds.

In order to understand which investors were informed I look at the information content revealed by market prices. I say that implied correlations are informative to the extent that they predict subsequent bond downgrades, controlling for agency rating at the time of transaction. I find that early prices of CMOs (i.e. prior to the pre-crisis mortgage boom that took place after June 2005) are informative, results which are in line with those of Ashcraft et al., 2011. Adelino, 2009 argues that this information content is absent from AAA tranches, implying the existence of an information differential between the unsophisticated senior investor and the sophisticated junior one (Boot and Thakor, 1993). In Gorton and Pennacchi, 1990, the former seeks information-insensitive tranches (in particular the AAA rated) while the latter can handle the information-sensitive ones (the junior tranches).[3]

I show that the presence of this information differential is essentially conditioned by the quality of the documentation on the underlying loans. More specifically, correlations implied

[3]The efficiency of this arrangement is discussed by Dang, Gorton, and Holmström, 2013. In particular, when information is costly this helps the market liquidity (Gorton and Ordonez, 2013).

from junior tranches are no more informative than those of AAA tranches for “low-doc deals, where the value of the asset is opaque. Conversely, AAA correlations are no less informative than junior ones within “full-doc deals, which are not opaque. Thus errors in computing default correlations in the running to the crisis were not the problem of AAA investors, but rather a problem of “low-doc” investors. Information deficiencies were thus essentially driven by the opacity of the underlying assets, which I capture through the completeness of documentation.

Some evidence remains that differential information exists in deals with intermediate levels of documentation. This shows that the agency problem between senior and junior investors remains, and that sophistication matters for intermediate opacity degrees. Ashcraft and Schuermann, 2008 argue there are two key information frictions between the investor and the originator of the securities. The first one, lack of investor sophistication, gives rise to differential information and eventually a principal-agent problem. This has been the main focus of the literature, as discussed so far. The second information friction, lack of due diligence about the quality of the assets, entails an incomplete information problem that constitutes the focus of this paper. The main contribution of this paper is to show how the two frictions highlighted by Ashcraft and Schuermann, 2008 interact, arguing that asset opacity has precedence over investor sophistication.

The results suggest that regulation interventions focusing on the agency problem, such as risk retention in the form of skin in the game, can be complemented by market transparency initiatives -achieving better documentation on the underlying loans-. To the extent that the incomplete information problem is easier to solve than differential information one, such transparency initiatives can be an effective instrument.

As explained in IOSCO, 2008 the key step in the rating process of a structured product is to determine the amount of subordination that will ensure a given rating, in particular a Standard & Poor’s AAA. This makes the subordination structure an essential aspect of the bondholder’s risk assessment, which yields alone do not reflect. Implied correlation aggregates yield and subordination percentage, taking into account the subordination structure together with the default and prepayment risk of the underlying loans.

Between yield and subordination, the latter seems to be the one whose information content is most sensitive to asset opacity. Whereas the informativeness of bond price does not vary much as a function of documentation completeness, that of the tranche subordination does. A fall in price is uniformly predictive of a downgrade, even controlling for rating. Instead, subordination is only predictive of downgrades for well documented deals. In line with this I find evidence that, controlling for probability of default, the amount of AAA issuance is decreasing in documentation completeness. The result is consistent with Skreta and Veldkamp, 2009, whose theory predicts that ratings are more likely to be inflated when assets are opaque.

The paper proceeds as follows. Section 1.1 relates this paper to the literature. Section 1.2 presents our data. Section 2.4 explains the copula model we use to infer default correlations. Section 1.4 presents the model estimates on our panel data. Section 1.5 lays out regressions to analyze the relative information content of ratings and prices. Section 1.6 concludes.

1.1 Literature

Low documentation loans give rise to opaque deals. From the loan level data on documentation completeness I construct an index of deal opacity. A number of papers have studied opacity in mortgage markets. JEC, 2007 documents a relative decline in the number of full documentation subprime loans in the running to the crisis. Keys et al., 2010 argue that the "low-doc" loans underperformed (in terms of defaults) relative to otherwise similar but better documented loans. This underperformance of low-doc loans is confirmed by the results of Kau et al., 2011. Moreover,Ashcraft, Goldsmith-Pinkham, and Vickery, 2010 use a loan-level measure of documentation completeness (similar to the one we use) to document the underperformance of "low-doc" deals. While our results are consistent with theirs in the sense of underperformance of low-doc deals, the performance we emphasize is on the information content reflected in market transactions. Finally, **AdelinoGerardiHartmanGlaser:16** find that investors deal with opacity by *skimming* the underlying loans; they look at the time to sale of loans in the secondary market, while we consider the channel of bond prices.

The collapse of CDO ratings after the crisis was arguably linked to subjective ratings (Griffin and Tang, 2012) and rating inflation (Benmelech and Dlugosz, 2010). Skreta and Veldkamp, 2009 argue that rating inflation worsens when assets are opaque, or "complex" to use their term (complexity being defined as the level of uncertainty about the true security value). We empirically corroborate their prediction that, controlling for risk attributes, low-doc deals see relatively more AAA issuance.

Disagreement is the starting point for differential information in market prices. By taking default probabilities as fixed and estimating default correlations, the implicit assumption in the Gaussian copula approach is that the main source of disagreement among investors in a given deal is the default correlation. The literature has examined the role of disagreement about other risk attributes such as prepayment speed (Carlin, Longstaff, and Matoba, 2014; Diep, Eisfeldt, and Richardson, 2016) or the probability of a crisis (Simsek, 2013). The prominence of Gaussian copulas in the CDO literature suggests that the primary source of disagreement across bonds in such a structure is the default correlation.

Default correlations can be inferred from default experience instead of from asset values. This is the approach followed by Cowan and Cowan, 2004; Servigny and Renault, 2002; Geidosh, 2014; Gordy, 2000; Nagpal and Bahar, 2001. By construction these estimators are more tightly linked to realized defaults than even the updated value of price-implied correlations. Though default-based measures are not directly comparable to ours (Frye, 2008), one study based on default experience worth noting here is Griffin and Nickerson, 2016. They infer rating agency beliefs about corporate default correlations by studying collateralized loan obligation (CLO). Their results suggest such beliefs were revised upwards after the crisis, but not sufficiently so when benchmarked against a default experience-based estimator accounting for unobserved frailty in the default generating process (Duffie et al., 2009). For our part we document that agency ratings adapted more slowly to the crisis than market prices.

The literature has historically attributed default clustering to joint dependence on a systematic shock (Bisias et al., 2012; Chan-Lau et al., 2009; Bullard, Neely, and Wheelock, 2009; Khandani, Lo, and Merton, 2013). We have followed this approach, using a Gaussian copula. Recent literature distinguishes two additional sources of default clustering: unobserved frailty (Duffie et al., 2009; Kau, Keenan, and Li, 2011; Griffin and Nickerson, 2016) and contagion (see appendix 1.6).[4] In particular Azizpour, Giesecke, and Schwenkler, 2016; Gupta, 2016 and Sirignano, Sadhwani, and Giesecke, 2016 suggest the contagion channel is important. In light of this literature, this paper is the first of several steps to understand which sources of default clustering are priced in mortgage markets.

1.2 Data

ABSNet collects monthly information about private label securitization deals, providing snapshots of all tranches inside a given deal between the time of origination and the end of 2016. For each month it provides updated information on rating, subordination, bond maturity and coupon. We collect all the snapshots available from each deal in their website. The tranches in their data are organized in a matrix format by increasing attachment point. From there we derive the detachment point for each tranche, and thus the waterfall of losses for the given deal.[5]

Between early cohorts (i.e. originated before June 2005) and late ones, we observe 71,915 tranches (linked to 5,790 deals, roughly 14 tranches per deal on average) for a total $4,380.3bn of originated securities.[6] Alt-A and subprime deals are the largest classes (see Table 1..7) which mostly built up in the running to the crisis (Gorton, 2009). Our estimation sample, composed of the 35,692 tranches issued before June 2005, is also composed mostly of suprime and Alt-A bonds, though the proportion is smaller than it is among late vintages.

CMOs are traded over the counter. Our price data comes from Thomson Reuters, which records the bid price and the mid from January 2004 onwards.[7] It only covers the series of prices for CMOs originated before and up to June 2005. Starting July 2009, our ABSNet also records transaction prices over time. Matching the two sources on CUSIP, year and month (keeping the nearest transaction to the rating observation date[8]) we check the consistency between the ABSNet price and the mid price in Thomson Reuters. We find a median absolute difference is $0.06 and a 99th percentile of $1.51, the difference being consistent with time differences in the date of the observation across sources. Between the two sources we have

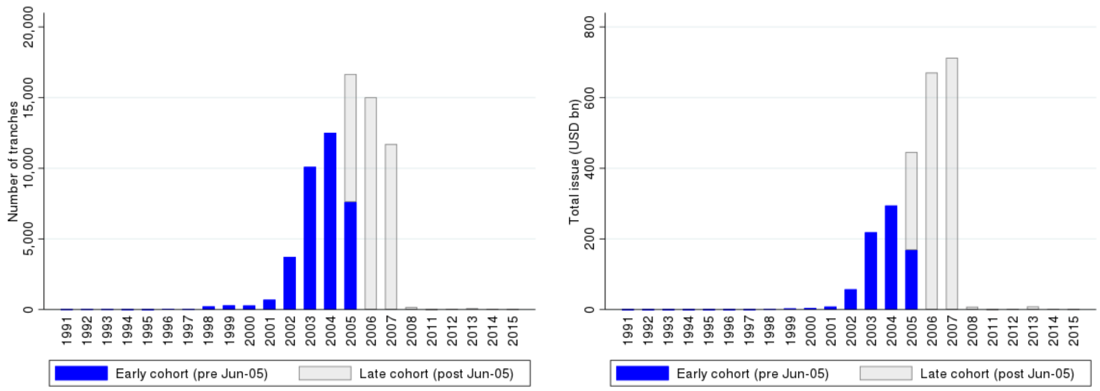
[4] For a review of recent literature on contagion see Bai et al., 2015.

[5] Some deals have more than one structure inside, each structure giving rise to its own subordination waterfall. We source each structure separately, and treat different structures as we would different deals.

[6] Adelino, 2009, uses 67,412 securities from JP Morgan's MBS database, for a total issue of $4,204.8bn (ours also includes post-crisis issuance). See Table 1..9. We follow his data cleaning procedures such as removing Interest Only, Principal Only, Inverse Floater and Fixed to Variable bonds from the sample.

[7] There is little variation in the spread (measured as the difference between the mid and the bid). The average is $0.17 on a par price of $100. The median is $0.06, same as the 25th and 75th percentiles.

[8] The average distance in days is 1.83, the median is 0 and the 99th percentile 53 days



(a) Number of tranches

(b) Total issue

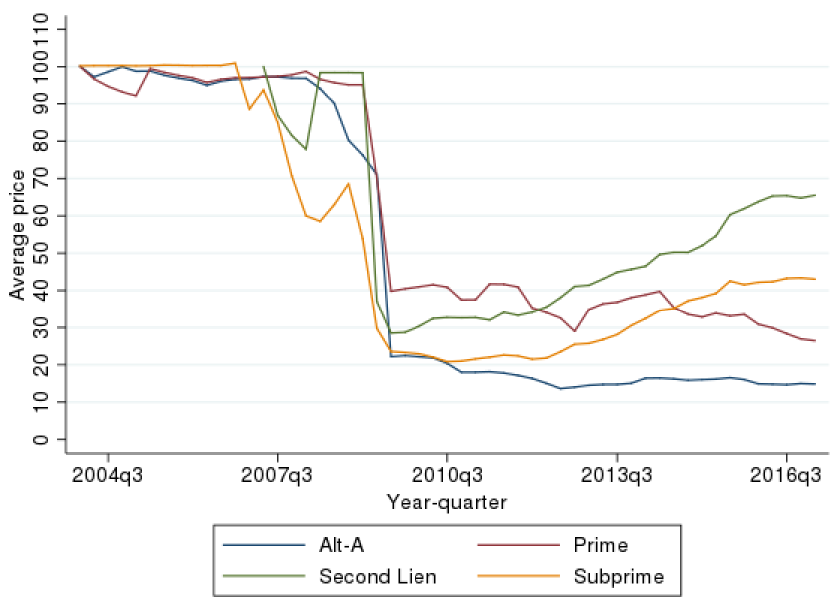
Figure 1.2.1: Number of tranches and amount issued by vintage year for private label collateralized mortgage obligations. Source: ABSNet bond data. The counts in our estimation sample (early vintages, prior to June 2005) are recorded in blue, while the numbers for late vintage tranches are illustrated in light grey.

a data gap, whereby for late (post 2005) cohorts we only have post crisis prices (after July 2009). For early cohorts, instead, we can track prices over time (the data provides as frequent as daily trading prices). Hence we will conduct the main analyses on the early cohorts.

The majority of issues in our sample are rated AAA, especially in terms of amount (see Figure 1..1). As Figure 1..2 shows, the bonds were mostly priced at par, or even slight premium, at the moment of origination, which we observe for the tranches originated in 2004 and 2005. This applies in particular to BBB bonds, which Deng, Gabriel, and Sanders, 2011 link to demand pressures from the surge of CDO markets. Within two months of issue prices have dropped and the variation in prices increased. Bonds then remain priced at a discount over subsequent trades. As Figure 1.2.2 shows, discounts are higher in the running to the crisis for AAA bonds, and within AAA they are higher for prime and Alt-A bonds. Over 2007 we see prices fall, but BBB bonds see a sharp fall compared to the relatively mild fluctuation in AAA prices. In comparison, AAA and BBB bond coupons have a similar pattern over time as shown by Figure 1.2.3. Aside from the wider fluctuations for BBB subprime and second lien bonds compared to the corresponding AAA ones, the difference over time across seniorities is less over prices than over coupons.

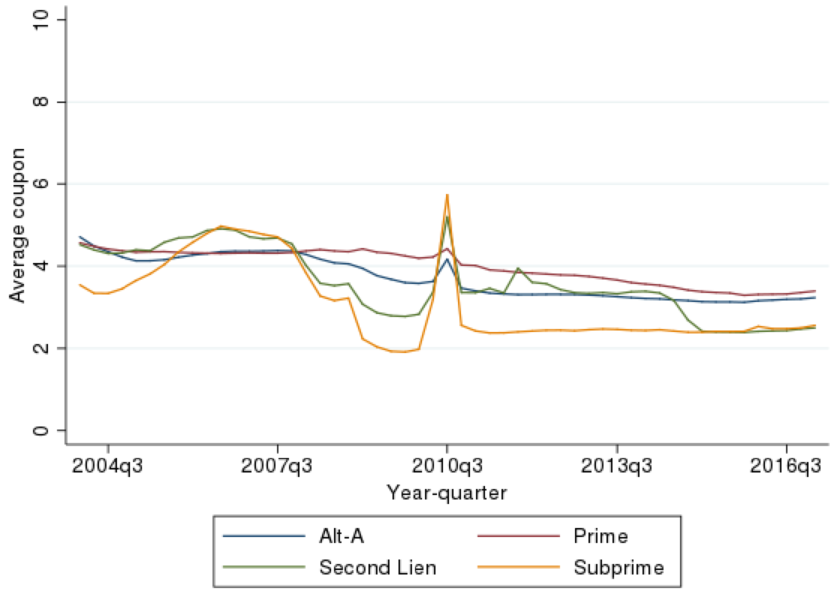
We now look at the deal subordination structure in our data. ABSNet provides the Standard & Poor's (S&P) rating, which is the main ordinal variable we use to capture the cash flow sequence among the bonds in a given deal. When the security has no S&P rating we use the one issued by Fitch, which uses the same grading scale. Figure 1.2.4 shows the average subordination percentage by rating at origination. Tranching becomes steeper as the rating increases, and Second Lien/Subprime deals in general require more subordination at

(a) Tranches rated AAA at origination

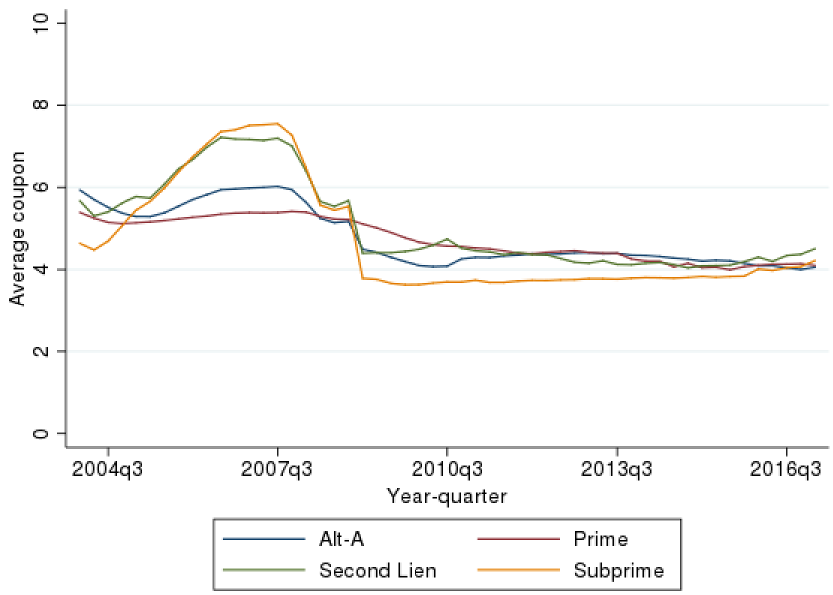


(b) Tranches rated BBB at origination

Figure 1.2.2: Average price by initial rating. Source: Thomson Reuters. For all the prices observed within a given month we use the closest to month end. The figure presents average price over trading time (for early vintages, prior to June 2005) controlling for initial rating.



(a) Tranches rated AAA at origination



(b) Tranches rated BBB at origination

Figure 1.2.3: Average coupon by initial rating. Source: ABSNet bond data.The figure presents average coupon rate over trading time (for early vintages, prior to June 2005) controlling for initial rating.

each rating grade. The average tranching structure lines up in general with the one Cordell, Huang, and Williams, 2012 obtain from Intex data (see Table 1..8 for a comparison), apart from relatively thicker AAA tranches in our sample. Intex contains data on so-called 144A deals,[9] which are not in our sample, aside from late vintage issues which are also excluded from our sample.

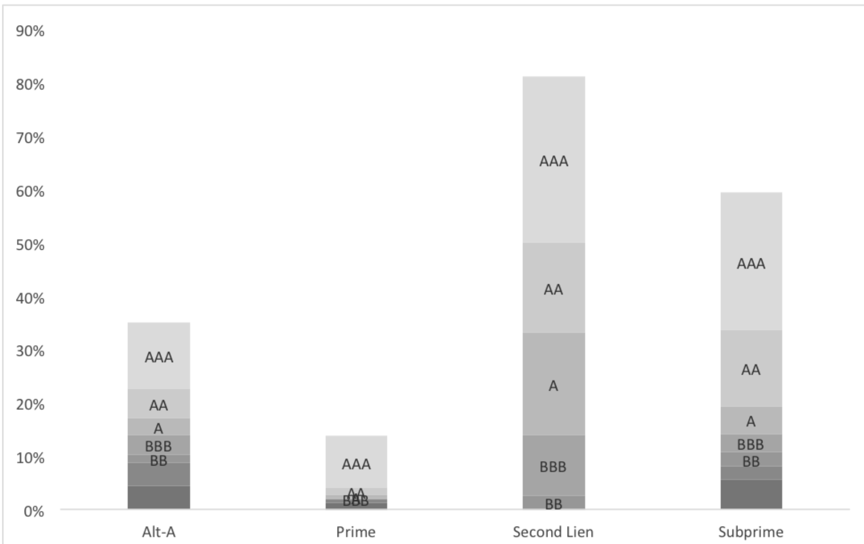


Figure 1.2.4: Deal structure. Source: ABSNet bond data. For our sample of early vintage deals, we look at the difference in subordination between tranches with consecutive S&P ratings. We then average the outcome by rating and asset type, aggregating at coarse grade level (see mapping in Table 1..20). This average difference is represented here, stacked by asset type.

Changes in subordination percentage take place over the cycle, though mostly for subprime deals. This is shown in Figure 1..3, which depicts the point-in-time difference in average subordination between AAA and BBB tranches. While the difference remains close to constant for Alt-A and prime deals, the difference rises for subprime deals in the running to the crisis, with a slight downward trend over time afterwards. In summary, among the tranche-level variables we use for the pricing model, i.e. price, coupon and subordination structure, the first two show exhibit more cyclical variation than the latter.

Besides the bond level data, we have loan origination and performance data on the underlying loans as recorded by ABSNet. Loans are linked to their respective deals. We start with a sample of 6,453,799 loans of which 3,509,785 are originated in 2005 or later. We have loan and borrower characteristics such as FICO score, owner occupancy, original

[9]Rule 144A of the Securities Act of 1933 allows private companies to sell unregistered securities to qualified institutional buyers.

loan amount and original LTV, which we will use in Section 1.3 to estimate default and prepayment hazard models.

The loan data also provides a documentation completeness indicator for each loan. Documentation completeness for a given loan is categorized as full, limited, alternative or no documentation. Figure 1.2.5 shows a distribution of the share (at the deal level) of loans with full documentation in our sample of vintages prior to June 2005. It suggests subprime loans were relatively better documented than Alt-A deals, with densities peaking around 0.7 and 0.35 approximately. Prime deals show a higher dispersion in terms of documentation completeness. In comparison, density plots on post-June 2005 issues suggest that documentation completeness deteriorated more among Alt-A, second lien and prime deals relative to subprime ones in the running to the crisis.

Including cases of partial and alternative documentation, we assign a documentation score to each loan (no documentation=0; partial=0.1; alternative=0.3; full=1). In comparison Keys et al., 2010 use percentage of completeness, which is equivalent to our index excluding the intermediate values. Linking loans to deals we average documentation scores into a deal level opacity index. Figure 1.2.6 presents the averages by asset type and vintage year. Note that Alt-A markets can only be characterized by low documentation levels -relative to other types- from year 2000 onwards. The downward slope in Figure 1.2.6 is in line reflects the decline in lending standards in the running to the crisis observed on subprime loans by Dell'Ariccia, Igan, and Laeven, 2012 and Keys et al., 2010.

Other data include dynamic covariates such as CBSA level home price indices from FHFA and interest rate data; we use the difference between the loan original interest rate -from ABSNet- and the original ten year Treasury rate -from FRED-. Using Treasury rates we also compute coupon gap (the difference between the ten year rate at origination and the current ten year rate). From Bloomberg we extract bond contractual maturities and weighted average life.

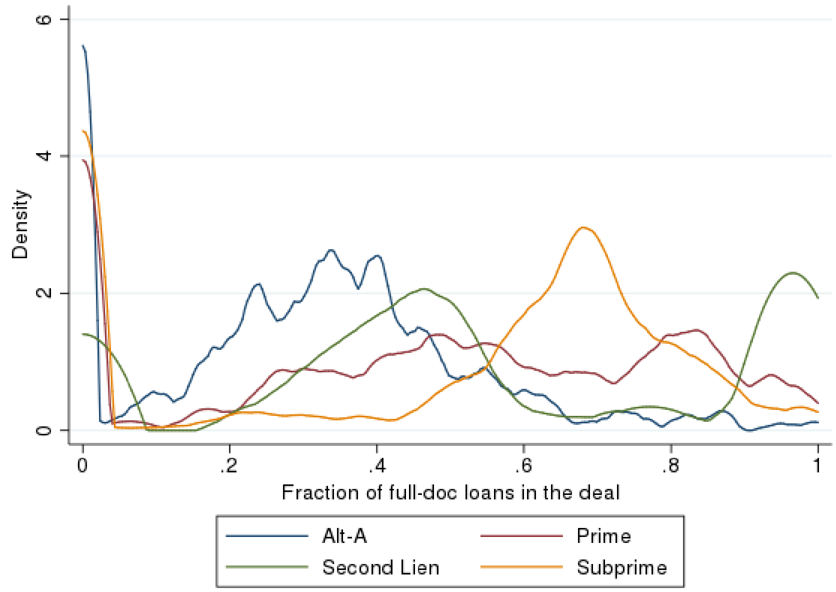
1.3 Modelling approach

We start by assessing the information content of different bond attributes considered so far (price, coupon and subordination) by estimating regressions of the form

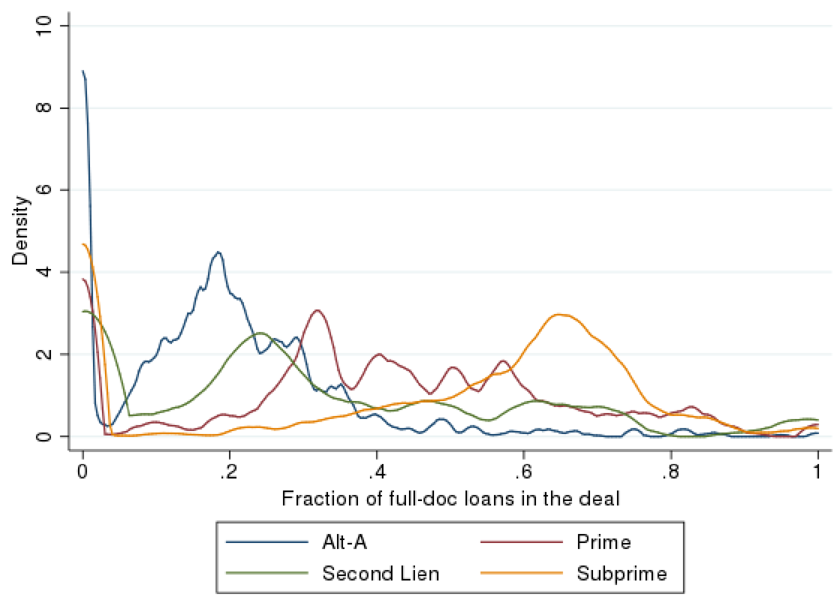
$$downgrade_{i,2009} = f(\alpha + \beta X_{i0} + \eta_{rating_{i0}} + \varepsilon_i) \tag{1.1}$$

where X_{i0} is a vector of bond attributes at origination such as price, subordination and coupon, controlling for deal vintage and tranche rating at origination.

Table 1.1 presents regression results for specification (1.1). A higher bond price is predictive of a lower probability of downgrade, and a higher percentage subordination has the same effect. Both are significant predictors of downgrades. A higher coupon significantly predicts lower downgrades, though this only holds for below-AAA bonds. Now we split the sample by value of the opacity index derived in Section 1.2, using four buckets of size 0.25. Table 1.2 shows that the effect most clearly driven by documentation quality is that of



(a) Originated before June 2005



(b) Originated after June 2005

Figure 1.2.5: Kernel density plot of the distribution of full-documentation loans by deal asset type. For each deal we obtain the percentage of fully documented loans associated to it. The figure represents a kernel density plot of the distribution of deals along this measure. A separate plot on vintages later than June 2005 is provided for comparison.

Figure 1.2.6: Average documentation index by vintage year. Source: ABSNet loan data. We assign a documentation score to each loan (no documentation=0; partial=0.1; alternative=0.3; full=1). Then for a given deal we compute the average documentation index, and present the averages by asset type and vintage year.

subordination percentage: the corresponding regression coefficient decreases monotonically from insignificant, for the lowest documentation indices, to negative and significant for the highest ones.

Comparing the subsample of AAA bonds and the rest, which we do in Table 1.3, we find evidence of this monotonicity of the regression coefficient on subordination percentage for both AAA bonds and the rest. So while the effect of price is always negative and significant and that of coupon depends on whether the bond is AAA at origination, the effect of subordination depends on the quality of documentation on the underlying loans as measured by our opacity index. In order to weigh the relative contribution of these different components we will price the bonds. The outcome of the pricing model, namely the implied correlation, works as a summary statistic of the variables considered so far.

We use the asymptotic single risk factor model implemented by the IRB approach in Basel II. Credit risk in this basic framework has two components, one systematic and the other idiosyncratic, so that correlation is captured by codependence on the realization of the systematic factor (Crouhy, Galai, and Mark, 2000). Due to the large number of observations we want to avoid the computational cost imposed by simulations. For that reason, and in order to use the benchmark model across the industry, we use the Large Homogeneous

	downgrade		
	(1)	(2)	(3)
	All	AAA only	Non-AAA only
Price	-0.0187***	-0.0457***	-0.00932***
	(0.00151)	(0.00299)	(0.00149)
Coupon	-0.123***	-0.0365	-0.184***
	(0.0178)	(0.0245)	(0.0240)
Subordination	-3.130***	-3.944***	-3.978***
	(0.268)	(0.565)	(0.310)
Observations	26,242	14,034	12,206
Rating at first transaction	Y	N	Y
Vintage year	Y	Y	Y

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.1: Regression results from running logit regression 1.1 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include price, subordination, coupon and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Column (1) includes all issues; columns (2) and (3) split the sample between bonds rated AAA at origination and the rest, respectively. Errors are clustered at deal level.

Gaussian Copula (LHGC) model (Brunne, 2006; D'Amato and Gyntelberg, 2005; Duffie and Singleton, 2012; Elizalde, 2005; McGinty et al., 2004; Tzani and Polychronakos, 2008).[10]

In the LHGC setup two assumptions apply: all loans in a given pool have the same (known) probability of default PD, and all have the same recovery rate RR. The homogeneity allows us to abstract from individual loan sizes, which we normalize to one. Consider a pool of N mortgages. Default times $\tau = \tau_1, \ldots, \tau_N$ are correlated random variables. Correlation is captured by the loading on one -exogenous- systematic factor S, which in our setting follows a standard normal distribution. In the one-factor Gaussian copula case the individual default probability is given by

$$p(s,T) := Pr(\tau \leq T | S = s) = \Phi\left(\frac{\Phi^{-1}(PD) - \sqrt{\rho}s}{\sqrt{1-\rho}}\right) \tag{1.2}$$

[10]Following Li, 2000 the Gaussian copula offered a conceptually simple framework for pricing structured securities,[11] which allegedly contributed to investor overconfidence and eventually set the stage for the financial crisis in 2007.[12]

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator			
Price	-0.0159***	-0.0200***	-0.0110***	-0.0169***
	(0.00606)	(0.00333)	(0.00267)	(0.00354)
Coupon	-0.142**	-0.0380	-0.117***	-0.0780*
	(0.0640)	(0.0304)	(0.0441)	(0.0466)
Subordination	0.00163	-1.857***	-4.016***	-5.722***
	(0.864)	(0.657)	(0.489)	(0.943)
Observations	2,489	5,513	7,073	5,049
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.2: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include price, subordination, coupon and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the average documentation index corresponding to the given deal. Errors are clustered at deal level.

where PD is the unconditional default probability. Defaults are independent conditional on the realization of the systematic factor S, i.e.

$$Pr(\tau_1 \leq t, \ldots, \tau_N \leq t | S = s) = \prod_{k=1}^{N} Pr(\tau_k \leq t | S = s)$$

which simplifies computations.

Total losses from the pool accumulate over time to $l(t) = \frac{1}{N}\sum_{k=1}^{N}(1 - RR)1_{(\tau_k \leq t)}$. The losses are distributed along the tranches from the deal. A given tranche's position in the waterfall is characterized by its lower and upper attachment points a and b where $0 \leq a < b \leq 1$. Its notional is a proportion $b - a$ of the total pool notional N. The losses borne by this tranche are given by

$$l_{[a,b]}(t) = \frac{[l(t) - a]^+ - [l(t) - b]^-}{b - a}.$$

This exposure to risk affects the expected payoff of the CMO tranche. Using the recovery rate, equation (1.2) yields the following estimate of expected losses within the $[a, b]$ tranche

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator - AAA only			
Price	-0.0352***	-0.0360***	-0.0347***	-0.0539***
	(0.00900)	(0.00529)	(0.00632)	(0.0127)
Coupon	0.0508***	0.0546	0.0919	0.118*
	(0.0161)	(0.0451)	(0.0575)	(0.0625)
Subordination	-0.0174	-2.774**	-2.014	-9.907***
	(1.622)	(1.229)	(1.881)	(3.612)
Observations	1,325	3,073	3,272	2,926
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y
	Downgrade indicator - not AAA			
Price	-0.0163**	-0.0129***	-0.00786***	-0.0113***
	(0.00714)	(0.00371)	(0.00250)	(0.00358)
Coupon	-0.367***	-0.167***	-0.201***	-0.156***
	(0.102)	(0.0475)	(0.0529)	(0.0603)
Subordination	-0.309	-2.648***	-4.501***	-4.193***
	(1.881)	(0.880)	(0.538)	(0.784)
Observations	1,038	2,248	3,757	2,111
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include price, subordination, coupon and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the average documentation index corresponding to the given deal. Errors are clustered at deal level.

by payment date T_i:

$$E[l_{[a,b]}(T_i)] = \frac{1}{b-a}\int_{-\infty}^{\infty} \frac{e^{-s^2/2}}{\sqrt{2\pi}} \left([(1-RR)p(s,T_i)-a]^+ - [(1-RR)p(s,T_i)-b]^+\right) ds \quad (1.3)$$

Duffie and Gârleanu, 2001 and Coval, Jurek, and Stafford, 2009a look at the sensitivity of expected recovery to default correlation. Figure 1.3.1 replicates the exercise in Coval, Jurek, and Stafford, 2009a by plotting expected recovery for each value of ρ, normalized by the value corresponding to $\rho = 20\%$.

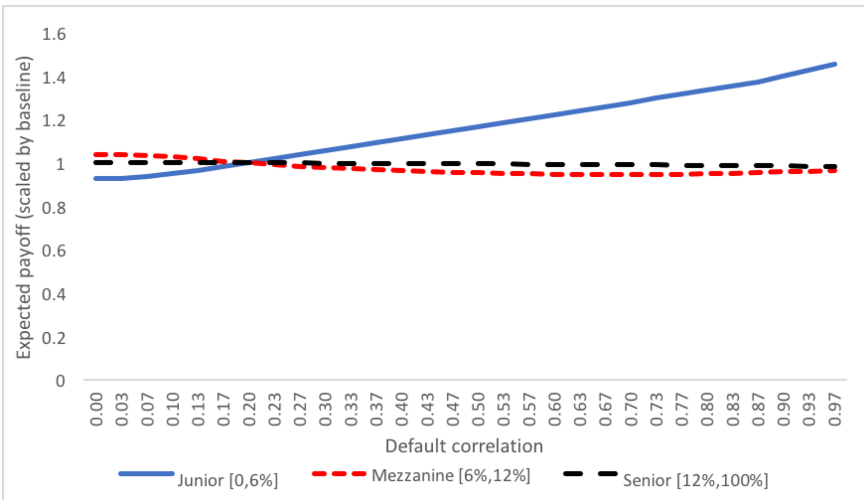


Figure 1.3.1: Sensitivity of a simulated CMO structure to default correlations. We plot the expected payoff within a given tranche, for each value of the underlying correlation ρ (parameters are PD=5% and LGD=50% as in Coval, Jurek, and Stafford, 2009a). The results are normalized by baseline estimate, based on the same parameters and a correlation $\rho = 20\%$. No prepayments are incorporated (i.e. SMM=0%) for comparability of outcomes.

Using payment dates $0 < T_1 < \cdots < T_m = T$ (where T is the maturity of the security), write the pricing equation of the security

$$\frac{V_{[a,b]}}{N(b-a)} = c\sum_{i=1}^{m} B(0,T_i)\Delta(T_{i-1},T_i)(1 - l_{[a,b]}(T_i)). \quad (1.4)$$

Formula (1.4) equates current price to the sum (in expectation) of two terms: the discounted cashflows from coupon payments and the residual value (after accounting for defaults) of principal outstanding. Here $B(t_1,t_2)$ discounts a payoff at t_2 to t_1, c denotes the tranche coupon and $\Delta(T_{i-1},T_i)$ is the time difference between two payment dates (for mortgage bonds we use $\Delta(T_{i-1},T_i) \equiv 1/12$).

The pricing equation is then $pN(b-a) = E[V_{[a,b]}]$. Writing $e_i^{[a,b]} = E[1 - l_{[a,b]}(T_i)]$ the following holds at origination:[13]

$$p_0 = c \sum_{i=1}^{m} B(0,T_i)\Delta(T_{i-1},T_i)e_i^{[a,b]} \tag{1.5}$$

The pool is exposed to prepayment risk.[14] As prepayments happen, the coupon rate is applied to the balance outstanding, while the prepaid amount is allocated across tranches according to the order specified in the prospectus. In the absence of data about the order of the cashflows for each deal, we make the simplifying assumption that prepayments are uniformly distributed across tranches.[15] We obtain

$$p_t = \sum_{i=t+1}^{m} B(t,T_i)e_i^{[a,b]} \prod_{k=t+1}^{i-1}(1 - SMM_k)\left(\underbrace{c\Delta(T_{i-1},T_i)(1 - SMM_i)}_{\text{coupon payment}} + \underbrace{SMM_i}_{\text{prepaid principal}}\right) \tag{1.6}$$

where SMM_k is the single month mortality rate at time k, and is given by the PSA. Given the unconditional default probability PD, the recovery rate RR and prepayment rate SMM_k, pricing equation (1.6) pins down a value of ρ, the market estimate of default correlation for the given pool of loans. Note that expression (1.2) is only defined for $\rho \in [0,1)$ and thus the existence of a solution to equation (1.6) is not guaranteed for an arbitrary choice of p and c. So instead of solving the equation, we solve

$$min_{\rho\in[0,1)} \left| p_t - \sum_{i=t+1}^{m} B(t,T_i)e_i^{[a,b]} \prod_{k=t+1}^{i-1}(1 - SMM_k)\left(c\Delta(T_{i-1},T_i)(1 - SMM_i) + SMM_i\right)\right| \tag{1.7}$$

Note that expected losses are monotonically increasing in default correlation ρ for the senior tranche, and monotonically decreasing for the junior tranche (see Figure 1.3.1). The mezzanine tranche behaves like a senior tranche for low correlations and like a junior tranche for high ones (Ashcraft and Schuermann, 2008; Duffie, 2008).[16] This gives the market estimate of default correlations which we now compute on our panel of security prices.

[13] Note that formula (1.6) implies that default occurs immediately after the following period payment.

[14] The Standard Prepayment Model of The Bond Market Association specifies a prepayment percentage for each month in the life of the underlying mortgages, expressed on an annualized basis. In Section 1.6 we will use the common assumption that prepayment speed is given by 150% PSA (see Figure 1..7).

[15] As an example, Duffie and Singleton, 2012 discuss two prioritization schemes (uniform and fast). Both imply prepayment cash flows are sequential over seniorities. We do not have deal-level information about the allocation of cash flows, and so we prepayments in a way that is neutral across deals.

[16] For those cases two minima could arise in principle (as would also be the case if solving for equation (1.6) instead of (1.7)).

Model parameters: default and prepayment

Probability of default and recovery rate

Our analysis is focused on expected losses (EL). Equation 1.3 uses the identity $EL = PD \times LGD$, which requires both default and recovery to be based on the same event. Recoveries in our data are based on liquidated values, hence the use of liquidation as the default event.

Figure 1..4 shows an increase in liquidation rates in the running to the crisis, though the trend is only upward sloping from 2005 vintages onward. Using securitization data from ABSNet and default experience from CoreLogics, Ashcraft et al., 2011 study MBS ratings and default rates in the running to the crisis. We look at the cumulative rate of liquidation, whereas they consider 90+ delinquency rates over 12 months. Alt-A default rates were roughly half those of subprime deals until early 2005, when both rates soared in the running to the crisis. By 2008, securitization issuance had dropped to the extent that errors bands in our sample overlap. One difference is that while the 90+ delinquency rate they report remains lower for Alt-A deals, we find that their cumulative liquidation rate, initially similar to that of prime deals, caught up with that of subprime in the running to the crisis.

From loss event data we can compute LGDs at deal level (see Figure 1..11 for a count of observations by vintage and asset type). Figure 1..5 shows that LGD was nearly monotonically increasing from 1990 onwards (except for a peak in 1996) in the running to 2007, so that the possibility that investors were adjusting their expectations of LGD over the cycle must be taken into account. However, for LGDs to be computed the full post-workout must be observed, which usually takes a substantial observation time after default. Recent advances in modeling LGDs with incomplete workouts (see Rapisarda and Echeverry, 2013) have been far from the norm in the industry, especially in the running to the crisis. We will apply the common assumption of constant LGD, using the long run (weighted) average on our sample of 59.87%, virtually the same as the 60% typically assumed in the literature (Altman, 2006; Brunne, 2006; Coval, Jurek, and Stafford, 2009b; Hull and White, 2004; Hull and White, 2008).

Investors' beliefs about default rates are elicited with a regression model establishing the likelihood of default as a function of loan covariates and estimated on default history. Similarly we use a proportional hazard model on a prepayment indicator to assess investors' beliefs about prepayment speeds. The model is estimated as a separable hazard model, treating observations representing default as censored as in Palmer, 2015 and Liu, 2016. Default and prepayment are termination reasons happening at a random time τ^{term}, whose intensity (for termination cause $term \in \{default, prepayment\}$) is given by equation (1.8).

$$\lambda_i^{term}(t) = \lim_{\epsilon \to 0} \frac{Pr_i(t - \epsilon < \tau^{term} \leq t \mid t - \epsilon < \tau^{term},\ X)}{\epsilon}. \tag{1.8}$$

Here i denotes loan, and t denotes time after origination. The density function in equation 1.8 is modeled as

$$\frac{\lambda_i^{term}(t)}{\lambda_0^{term}(t)} = \exp(X_{it}'\beta^{term}) \tag{1.9}$$

where$\lambda_0^{term}(t)$is the baseline hazard function that depends only on the time since origination t. Covariates in X_{it} include loan attributes (loan amount, coupon gap relative to 10 year constant maturity Treasury, LTV, prepayment penalty indicator), agent characteristics (FICO score, owner occupancy) and variables at the CBSA level such as home price appreciation and unemployment rate. The exponential model specified in equation 1.8 has a continuous time specification. To estimate it on discrete time data we accumulate the intensity process λ over time intervals per equation (1.10).

$$Pr_i(t < \tau^{term} \mid t-1 < \tau^{term}) = \exp\left(-\int_{t-1}^{t} \lambda_i^{term}(u)du\right) \tag{1.10}$$

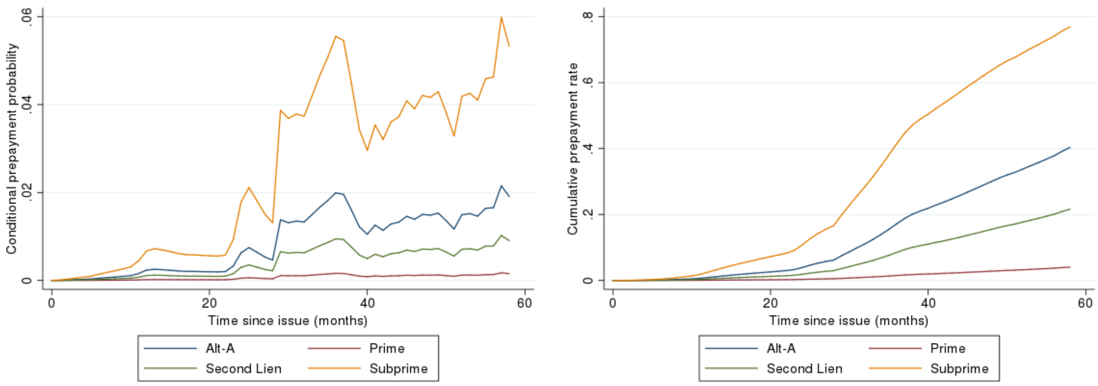
This leads to the complementary log-log specification in equation (1.11):

$$Pr_i(t < \tau^{term} \mid t-1 < \tau^{term}) = \exp(-\exp(X_{it}'\beta^{term})\lambda_0^{term}(t)) \tag{1.11}$$

We estimate specification (1.11) on data up to the end of 2004, with month since origination fixed effects to obtain the hazard functions over the first 60 months of the loan. We document the results in Table 1..11 and plot the resulting prepayment rates on Figure 1.3.2. We find that adjustable rate mortgages are both more likely to default and prepay than fixed rate types. Subprime loans are the asset type most likely to default. In terms of prepayment hazard, there is no significant difference across asset types other than prime loans being less subject to prepayment than other types.

We now compare our results with the ones obtained by Liu, 2016 who uses the same model to estimate default and prepayment hazard rates on loans backed by the government-sponsored entities (Fannie Mae and Freddie Mac).[17] On one hand, we find the same sign for the effect of FICO score, the difference between the original loan interest rate and the original 10 year rate and the unemployment rate. Moreover, in terms of default hazard we find similar effects of LTV and home price appreciation.

[17] Adding late originations (up to 2007) we find a number of similarities. The main difference that arises is that now subprime loans can be seen to be prepaying significantly more than other types, and significantly more than early vintages. This suggests that the link between subprime origination and home prices through prepayments was specific to the pre-crisis boom rather than a constitutive characteristic of subprime loans from their inception. Macroeconomic factors such as home price appreciation and unemployment exhibit a similar effect on defaults and prepayments when adding late vintages. Instead, for coupon gap there is a change compared to the early sample. The coupon gap, i.e. the change in 10 year rates between origination and present, reflects stronger incentives to refinance. The expectation is that this leads to a higher probability of prepayment and a lower probability of default, which we see once we add late cohorts but not in the early sample.



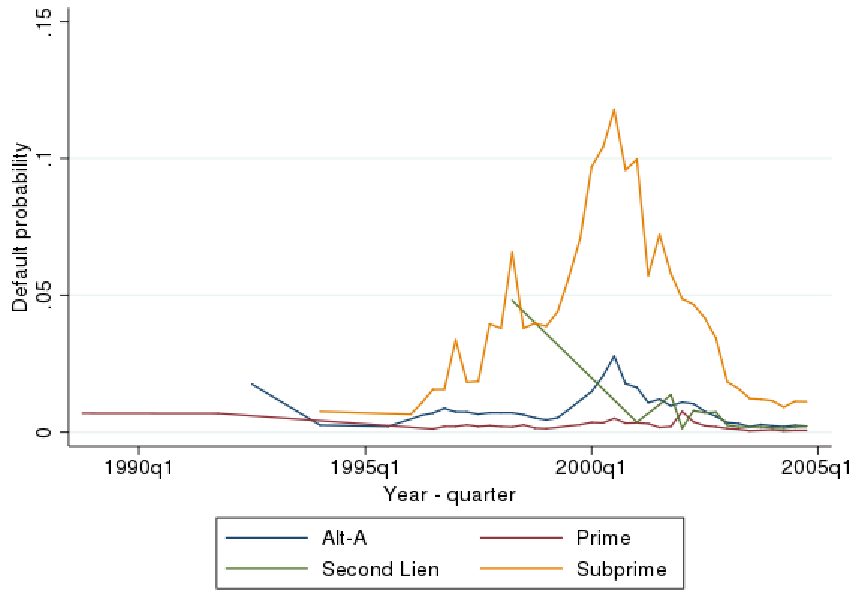
(a) Prepayment hazard (b) Cumulative prepayment rate

Figure 1.3.2: Marginal and cumulative prepayment rates implied from the model (1.11), as summarized in Table 1..12. Using loan covariates at origination, prepayment hazard rates are computed at the loan level. Averages are computed by asset type and month after origination, and plotted here.

On the other hand we find a few differences, mostly about the link between home prices and prepayment rates. Liu, 2016 finds that home price appreciation increases prepayment hazard while we find the opposite. Similarly, he finds that higher LTV reduces prepayment hazard while we find no clear link. As discussed by Gorton, 2009, while the prepayment option is always valuable for prime, 30-year fixed rate mortgages (i.e. if house prices rise borrowers build up equity), for subprime loans lenders hold an implicit option to benefit from house price changes. Table 1..11 shows prepayment penalties, this being the way in which the lender exercises its option, are a strong deterrent against this termination type.

The break-even probabilities of a crisis computed by Beltran, Cordell, and Thomas, 2017 from CDO prices show a decrease from early cohorts (pre 2006 per their definition) to late ones, which suggests a relatively high risk premium was charged in early cohorts. Though there are no studies on risk premia in mortgage markets, we can benchmark our parameters against the corporate market. (Berndt et al., 2005) imply actual and risk-neutral probabilities from CDS market quotes. They find that the corresponding coverage factors (ratio of risk neutral probability to real probability) oscillate between 1.5 and 3.5 over time, between 2002 and 2003. We use a coverage ratio of 3.[18]

[18]Heynderickx et al., 2016 quantify coverage factors from CDS quotes of European corporates and find that they range between 1.27 for Caa (Moody's) ratings to 13.51 for Aaa ones on pre-crisis data. Like Heynderickx et al., 2016, Denzler et al., 2006 argue that risk spreads exhibit a scaling law, whereby risk premia are decreasing in the probability of default. The results in Table 1..21 imply coverage ratios between 2.03 for subprime deals and 3.27 for Alt-A ones, in line with the literature.



(a) Probability of default

Figure 1.3.3: Probability of default implied from the complementary log-log model, estimates of which are in Table 1..12. Using loan covariates at origination, default probabilities are computed at the loan level. Averages are computed by asset type and month after origination, and plotted here.

Using the model in Table 1..12 we predict prepayment hazards and default probabilities at the loan level, and average them at the deal level. Both the default probability and the hazard rate are estimated deal by deal (in Section 1.6 we use a constant PD and prepayment speed, as a robustness check). As for the prepayment hazard, we will use the full schedule in order to estimate the average prepayment speed for the given deal over the first 60 months. As Figure 1.3.2 illustrates, subprime loans have the highest prepayment rates, followed by Alt-A loans. They also have the highest default probabilities, as shown in Figure 1.3.3. We use the model-implied PDs from Table 1..12 (see Figure 1.3.3) and include them as controls in our regressions.

Prepayments are contractually allocated across classes per the deal prospectus. Although we don't have information at deal-tranche level, a proxy we can look into is the rating at first transaction. We split prepayment rates by tranche rating, assuming that prepayment behavior is driven by this attribute. Although we do see mezzanine tranches dropping faster than senior ones, the ordering is not monotonically increasing as BBB tranches are prepaying faster than AA ones (see Figure 1..8). For that reason we do not assume prepayments are sequential from AAA to D tranches.

Another model input is the residual maturity of the contract at the time of pricing. We source contractual maturity from Bloomberg, which for most bonds is close to 30 years. These figures are high (16.27 years difference on average, on a sample of 5,507 tranches) compared with realized maturity (defined as the first observation where the tranche balance is zero). Figure 1..6 also suggests that bonds do not live that long on average. Adelino, 2009 uses weighted average life (WAL) instead of contract maturity, which is closer to the realized maturity. We also source WAL for a sample of our loans where we could find it, but found that WALs are low compared to realized maturities in the data (the average difference is 6.77 years on a sample of 16,894 tranches, see Figure 1..9 for a further breakdown of the difference). We will use contractual maturity, relying on the assumption of 150% PSA to achieve an accurate reduction of tranche balance over time.

The model in Table 1..12 incorporates all observations over time, applying them both prospectively and retrospectively to price bonds over time. In reality, agents' expectations about default evolve over time, especially as the business cycle unfolds. As an example take home prices, which fluctuate over the cycle. As Table 1..13 shows, home price appreciation is the variable whose effect on defaults changes the most over the cycle. In particular, the negative relationship between price appreciation and defaults documented in Table 1..12 is an average between the positive effect recorded in the early years of the sample (up to 2002) and the negative effect in subsequent years. We expect that the effect this has on the pricing model is small, given that over the times of the prices we are interested in (mostly 2004 and 2005) the coefficients in Table 1..13 tend to be close to those in Table 1..12.

Loan performance data gives a basis for consensus about probability of default, loss given default and prepayment speed. Default correlation is instead a parameter market participants are more likely to disagree about[19]. Seeing these disagreements as the starting point for differential information, we will use the pricing model from Section 2.4 to generate a summary statistic that acts as a signal of future downgrades, and study how asset opacity drives the informativeness of the signal.

1.4 Implied default correlations from CMO data

For a given bond we compute its compound correlation ρ given the coupon rate c, market price p, attachment and detachment points $a \geq 0$ and $a < b \leq 1$. The probability of default and prepayment speed are estimated per Section 1.3. The recovery rate is $RR = 60\%$. We use the discount rate $r = 4.27\%$, the average 10-year constant maturity treasury (annual) rate between 1995 and 2015. The numerical computations of loss probability are evaluated using a trapezoidal rule, which Brunne, 2006 deems faster than Gauss-Legendre and Gauss-Hermite methods. Figure 1..13 provides a summary of observations.

The distribution of individual outcomes is bimodal (see Figure 1..12). The extreme prices suggest there is a role for market incompleteness as in Andreoli, Ballestra, and Pacelli,

[19] "Currently, the weakest link in the risk measurement and pricing of CDOs is the modeling of default correlation." citeDuffie:08

2016 and Stanton and Wallace, 2011. Tzani and Polychronakos, 2008 find that in CDS markets model correlations would often have had to exceed 100% in order to price supersenior tranches, which is suggested by Figure 1..17. Figure 1..13 also shows evidence of a correlation smile in prices both before and after the crisis.[20]

Using a one factor Gaussian copula model, Buzková and Teplỳ, 2012 analyze prices of the 5-year, North American investment grade CDX (V3) index between September 2007 and February 2009. They report that for synthetic CDOs, implied correlations show a large increase, from 0.15 to 0.55 on average over that time period. In comparison, we observe a significant increase over the same period, though of smaller magnitude (from 0.89 to 0.93). Breaking the change by asset type we see an increase for Alt-A tranches (from 0.81 to 0.97, significant at 99%) and for subprime deals (from 0.85 to 0.89, significant at 99%) and no change for prime ones (0.93). The upward adjustment was thus the largest for Alt-A issues (see Figure 1..14). In terms of seniorities, the difference observed by Buzková and Teplỳ, 2012 over the crisis is mainly driven by mezzanine tranches (7%-10% and 10%-15%). Figure 1..13 also suggests the increase in correlations is larger among intermediate seniorities.

We now consider the trend over time (see Figure 1.4.2). Ratings were mostly stagnant ahead of the crisis, especially for AAA tranches, in comparison with default correlations. BBB tranches even see an improvement in ratings before the crisis while correlations are increasing (except for subprime deals, which see both downwards and upwards changes). The sharpness of rating downgrades suggests this is a concern for BBB tranches. Griffin and Tang, 2012 argue that AAA ratings were inflated in CDO securities, with optimistic ratings applied to a large share of bonds issued. Because CDOs are mainly composed of CMO tranches, a potential channel for rating inflation in AAA CDO tranches is rating inflation in the underlying BBB tranches, which were on average being upgraded. This gives a possible channel for ratings inflation that differs boom time originations.

The graphic evidence presented so far suggests there is an adjustment of correlations over time, and that ratings do not lead correlations at either maturity. Whether this means investors learn faster than ratings agencies will be revealed by the informativeness of default correlations relative to that of agency ratings. Using our panel data on prices and ratings,

[20] The correlation smile is an artifact from the compound correlation method (O'Kane and Livesey, 2004). A method that is used to derive increasing correlations is the base correlation, which is computed as follows: let the attachment points in the full waterfall be given by $(b_1, \dots, b_n)$, where $b_n = 1$. First, solve 1.6 for the tranche $[0, b_k]$, $k = 1 \dots n$. This gives an estimate of $e_i^{[0,b_k]}$. Using the identity

$$(b-a)e_i^{[a,b]} = be_i^{[0,b]} - ae_i^{[0,a]},$$

the expected losses in tranche $[a, b]$ can be sequentially computed along the waterfall: once the $[b_{k-1}, b_k]$ tranche has been priced, the following one can be priced using

$$(b_{k+1} - b_k)e_i^{[b_k,b_{k+1}]} = b_{k+1}e_i^{[0,b_{k+1}]} - b_k e_i^{[0,b_k]}.$$

Base correlations price all tranches in a deal simultaneously, and thus do not use base correlations because we are pricing tranches that trade separately over time.

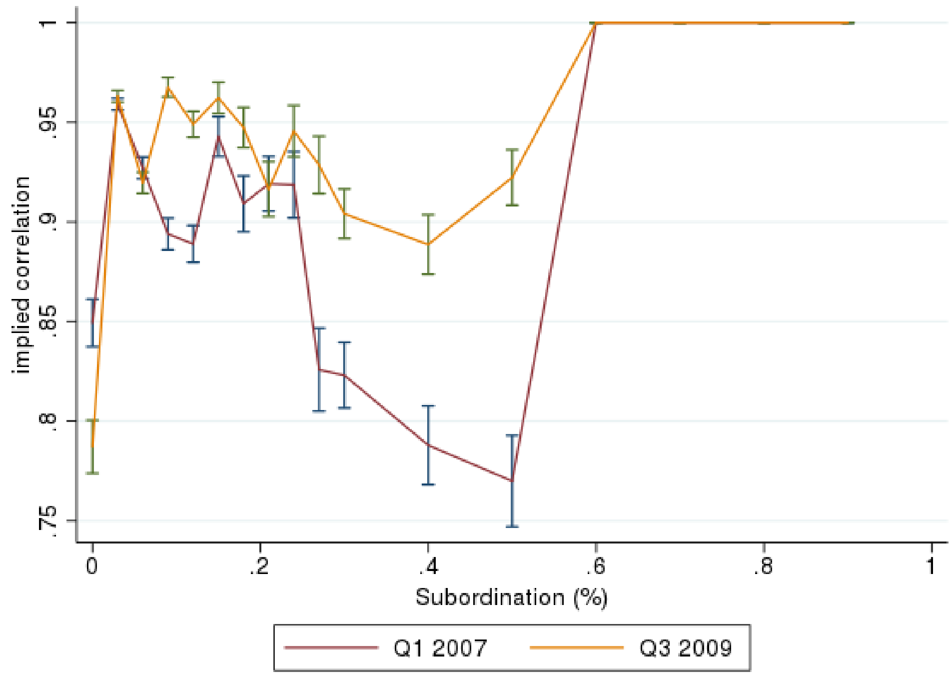
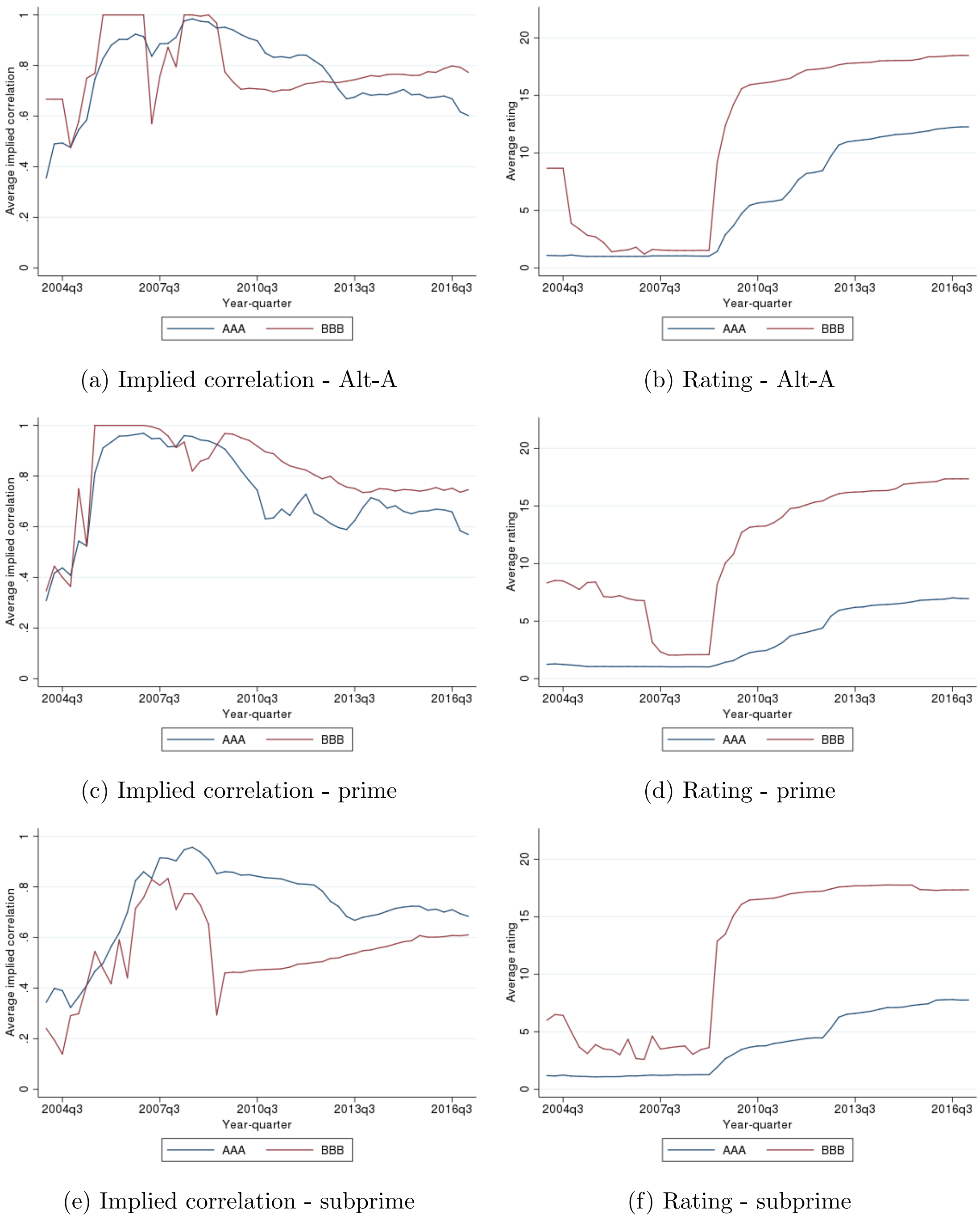


Figure 1.4.1: Average correlation plotted against tranche subordination percentage, on two given dates. We use the sample of early vintage bonds (originated prior to June 2005). Subordinations are assigned to 10 equally spaced bins. Within each subordination bin we plot the average correlation, along with vertical whiskers representing the standard error of the average.

the next section will study the information content of market prices, as captured by implied correlations, about posterior bond outcomes.

1.5 The information content of implied correlations

This section will focus on whether correlations implied from early prices are informative of subsequent downgrades. We start with the sample of early vintages -prior to June 2005- for which we have price data prior to the crisis. Using this data we replicate the findings by Ashcraft et al., 2011 that market prices contain information about bond performance which is not captured by the agency ratings. Then we replicate the result in Adelino, 2009 that the information content is a priori less significant for AAA tranches than for non-AAA tranches. The dependent variable is whether bond i was downgraded by December 2009. We start with a logit specification similar to that in Adelino, 2009, where bond downgrade



(a) Implied correlation - Alt-A

(b) Rating - Alt-A

(c) Implied correlation - prime

(d) Rating - prime

(e) Implied correlation - subprime

(f) Rating - subprime

Figure 1.4.2: Performance of early vintage tranches: average implied correlation and average rating for bonds originated before June 2005. For a given we compute the implied correlation, at each point in time. The average is taken by transaction period, by coarse rating at origination (AAA=1,..., BBB=4,..., D=8).

is the dependent variable. More specifically we write

$$downgrade_{i,2009} = f(\alpha + \beta\rho_{i0} + \eta_{rating_{i0}} + \gamma X_{i0} + \varepsilon_i). \tag{1.12}$$

The independent variable of interest is the implied correlation at first transaction ρ_{i0}. High correlations are detrimental to senior bondholders but beneficial to subordinate ones (Duffie and Gârleanu, 2001). In line with this we expect that (except for bonds with zero subordination percentage, which we do not often observe) a higher implied correlation should predict a more likely downgrade. We control for rating at origination using dummy indicators and for vintage year. Also we cluster standard errors in all tests at the deal level, to control for the fact that several classes in the same deal are often (down)graded at the same time.

The results in Table 1.4 replicate the findings by Ashcraft et al., 2011 that, though statistically significant, ratings at origination are not sufficient for implied correlations (in their case, coupon premium) in predicting subsequent bond downgrades. Their proxy for the bond price is the coupon premium to treasury, the hypothesis being that higher premium is reflective of more risk and thus of more downgrades. Our implied correlation measure gives a similar result. We find a positive, significant coefficient, so that higher implied correlation increases the likelihood of downgrades. Table 1.4 breaks down this result between bonds initially rated AAA and the rest. While the coefficient for correlation at first transaction remains significant for grades below AAA, implied correlations seem to have no predictive power in terms of bond downgrades, similar to the findings in Adelino, 2009.

We use our opacity index to break down the sample by increments of 0.25, and present the results in Table 1.5. We find a ranking along the index similar to the one discussed in Section 2.4, whereby the coefficient on implied correlations is monotonically increasing in the value of the opacity index, from insignificant at 10% for tranches below 0.25 to positive and significant at 1% for tranches above 0.75.

Breaking down the results between AAA tranches and others shows a similar pattern. Moreover, for tranches where the documentation index is above 0.5 we have that implied correlation is predictive of bond downgrades. Seen together, the results suggest that uninformed investors are not so much those in AAA tranches as those subject to poorly documented loans.

As a robustness check, we run the same set of regressions as before, using the deal level average correlation (clustering errors at deal level) instead of the tranche implied correlation. We control for initial prices, coupons and subordinations. The results, shown in Table 1..15, suggest that correlation loses its predictive power when averaged across the deal. The average at rating level, instead, retains some predictive power about subsequent downgrades. Breaking the results down by opacity index in Table 1..16, we find the same monotonicity in predictiveness of implied correlations, though the coefficient becomes significant only for the highest values of the documentation index. However, once we break down the results between AAA and sub-AAA tranches in Table 1..17, only AAA tranche implied correlations are predictive (still, only in the highest documentation index values). In all these tables, the monotonicity property observed before is best represented by the subordination percentage.

	downgrade		
	(1)	(2)	(3)
	All	AAA only	Non-AAA only
Correlation at first transaction	0.414***	0.299	0.268***
	(0.0629)	(0.201)	(0.0644)
Model-implied PD	2.294**	4.308	1.503
	(0.922)	(3.648)	(1.023)
Observations	28,991	16,618	12,371
Rating at first transaction	Y	N	Y
Vintage year	Y	Y	Y
Asset type	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Regression results from running logit regression 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default, as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Column (1) includes all issues; columns (2) and (3) split the sample between bonds rated AAA at origination and the rest, respectively. Errors are clustered at deal level.

Low-doc assets should in principle require a form of compensation: all else constant, a sophisticated investor requires more subordination when the underlying assets are opaque. Instead, Skreta and Veldkamp, 2009 predict that rating inflation is worse when assessing the true value of the asset is difficult (making ratings noisier and more varied). For their result to hold, investors must be unable to infer the rating selection bias. Similarly in our case, investors who are unaware of the deficiency in documentation are more likely to be subjected to inflated ratings. Table 1..18 provides evidence that AAA share at origination is decreasing in our opacity index (controlling for the model-implied probability of default). This suggests that unsophisticated investors select into low-doc deals, where rating inflation is more likely to occur.

1.6 Conclusion

Two key frictions take place in securitization markets between the investor and the securitizer. Though there is a role for a proxy of investor unsophistication, namely whether the bond is AAA-rated at origination, there is an important role of asset opacity, which we capture using a deal-level index of documentation completeness. We observe less of a dif-

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator			
Correlation at first transaction	0.243	0.605***	0.476***	0.569***
	(0.250)	(0.200)	(0.102)	(0.135)
Model-implied PD	0.381	13.60	4.331	4.225*
	(1.675)	(10.51)	(3.000)	(2.521)
Observations	2,723	6,285	7,808	5,565
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the value of the documentation index corresponding to the given deal. Errors are clustered at deal level.

ferential in information content across seniorities than across low-doc assets and "full-doc" ones. We show that the latter exhibit better information content across the rating spectrum. In particular, AAA implied correlations are no less predictive than the rest when the bond comes from a deal with a high standard of documentation.

We link the information content of bond trades to the opacity on the underlying collateral, saying that more opaque loans convey less market information. The results suggest that unsophisticated transactions select into low-doc deals. In line with this, we provide evidence that more opaque deals tend to issue a higher proportion of AAA bonds, controlling for risk attributes of the deal. The results are consistent with ratings inflation.

Implied correlations are large in subprime deals compared to other asset classes, which reflects a design feature of subprime loans that made them jointly dependent on house prices. We capture this within a systematic factor framework. However, investors could be underestimating aspects of default clustering different from systematic risk. Following Griffin and Nickerson, 2016, who argue rating agencies underestimate frailty risk, the question of whether contagion risk (see Appendix 1.6) is priced remains open.

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator - AAA only			
Correlation at first transaction	1.018	0.430	1.647***	0.842***
	(0.703)	(0.599)	(0.627)	(0.321)
Model-implied PD	47.95	-13.93	12.91***	3.301
	(48.60)	(45.34)	(4.648)	(2.970)
Observations	1,529	3,765	3,975	3,429
Rating at first transaction	N	N	N	N
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y
	Downgrade indicator - not AAA			
Correlation at first transaction	0.0485	0.370**	0.314***	0.353**
	(0.283)	(0.155)	(0.109)	(0.158)
Model-implied PD	-2.323	26.14**	1.906	5.083
	(2.661)	(10.85)	(2.607)	(3.180)
Observations	1,045	2,289	3,787	2,124
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

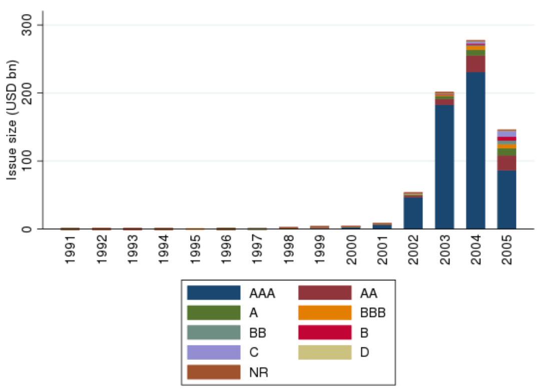
Table 1.6: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the value of the documentation index corresponding to the given deal. Errors are clustered at deal level.

Appendix

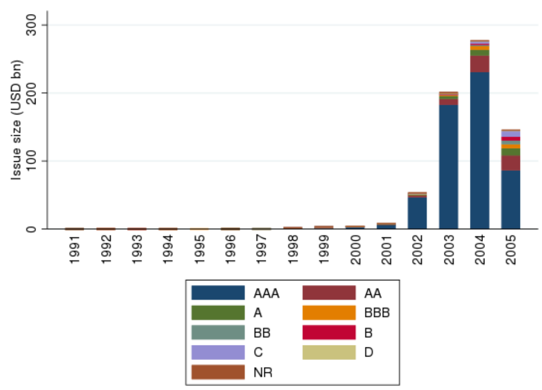
Supplemental graphs and tables

Asset type	After Jun-05		Before Jun-05	
	Origination ($bn)	Count	Origination ($bn)	Count
Alt-A	1,179.0	16,837	557.7	11,000
Prime	621.7	9,097	557.9	14,759
Second Lien	64.7	478	19.0	408
Subprime	660.0	9,811	720.2	9,525
Total	2,525.4	36,223	1,854.8	35,692

Table 1..7: Issued amounts and counts by asset type.



(a) Number of tranches



(b) Total issue

Figure 1..1: Number of tranches and amount issued by vintage year for private label collateralized mortgage obligations. Source: ABSNet bond data. For our sample of early vintages (prior to June 2005) we provide the distribution by (coarse, see Table 1..20) initial rating.

Data cleaning

Bond data

We start with 16,397,826 panel observations, corresponding to 127,963 tranches. I remove data entry errors such as subordination percentages larger than one. In those cases all observations for the month (all tranches linked to the deal involved) are removed so as to ensure computations of the tranching structure are correct.[21] We follow Adelino, 2009 in

[21]I manually computed subordination percentages on a random sample of deals to check the calculations by ABSNet.

	Our sample		Cordell, Huang, and Williams, 2012	
rating	Prime/Alt-A	Second Lien/Subprime	Prime/Alt-A	Second Lien/Subprime
AAA	10.8%	25.7%	6%	23%
AA	3.4%	14.3%	3%	13%
A	3.0%	5.9%	2%	8%
BBB	2.9%	4.0%	1%	4%

Table 1..8: Subordination percentage by tranche rating - comparison. The figures computed using ABSNet data are derived by aggregating the subordination percentages at orgination as given in Table 1.2.4. Our sample contains only early vintages (prior to June 2005) while Cordell, Huang, and Williams, 2012 use late vintages as well.

Year	ABSNet sample		Adelino, 2009	
	Origination ($bn)	Count	Origination ($bn)	Count
≤2002	319.3	5,438		
2003	470.5	10,120	496.5	8,574
2004	677.4	12,519	767.3	11,460
2005	904.5	16,684	1,058.5	17,135
2006	1,038.0	15,022	1,080.4	18,206
2007	939.4	11,716	802.1	12,037
≥2008	31.2	177		
Total	4,380.3	71,676	4,204.8	67,412

Table 1..9: Origination amounts and counts at origination, by vintage year, compared to the sample in Adelino, 2009.

	(1)	(2)
Asset type	Early vintages	Late vintages
Alt-A	7.5%	19.5%
Prime	2.3%	6.6%
Second Lien	7.2%	25.8%
Subprime	14.8%	30.5%
Observations	4,060,698	631,793

Table 1..10: Liquidation rates from the loan sample. Column (1) calculates the percentage of loans linked to early vintage deals (before June 2005) that are liquidated. Column (2) calculates the same ratio for late vintage loans.

	with data up to 2004		with data up to 2007	
	(1)	(2)	(3)	(4)
	Default	Prepayment	Default	Prepayment
log(FICO)	-1.468***	1.408***	-2.076***	0.305**
	(0.157)	(0.155)	(0.199)	(0.12)
owner occupied	0.039	-0.024	-0.098*	0.024
	(0.05)	(0.02)	(0.054)	(0.02)
original r - original 10 year rate	0.475***	0.249***	0.252***	0.066***
	(0.01)	(0.017)	(0.011)	(0.006)
log(original amount)	0.421***	0.257***	0.143***	0.02
	(0.043)	(0.031)	(0.041)	(0.026)
log(original LTV)	0.439***	-0.007	0.183***	0.069***
	(0.043)	(0.036)	(0.033)	(0.02)
prepayment penalty	-1.866***	-1.034***	-0.914***	-0.950***
	(0.08)	(0.073)	(0.031)	(0.025)
adjustable rate mortgage	0.655***	0.493***	0.367***	0.467***
	(0.062)	(0.047)	(0.038)	(0.015)
log(Cumulative HPA)	-8.398***	-7.780***	-6.482***	-2.474***
	(1.041)	(0.963)	(0.652)	(0.41)
coupon gap	0.400***	0.120*	-0.255***	-0.144**
	(0.05)	(0.062)	(0.04)	(0.06)
unemployment	0.330***	0.320***	0.201***	0.319***
	(0.072)	(0.075)	(0.068)	(0.075)
Asset type: Prime	-1.008***	-0.147***	-1.130***	-0.603***
	(0.078)	(0.027)	(0.078)	(0.033)
Asset type: Second Lien	-0.580***	0.124	0.843***	0.385***
	(0.142)	(0.079)	(0.064)	(0.028)
Asset type: Subprime	0.504***	-0.021	1.113***	0.201***
	(0.053)	(0.05)	(0.037)	(0.02)
CBSA FE	Y	Y	Y	Y
Month since origination FE	Y	Y	Y	Y
Observations	68,634,789	76,206,672	121,236,208	126,625,633

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1..11: This table shows estimates using the maximum likelihood estimation of the complementary log-log specification in (1.11), using a nonparametric baseline hazard, on the loan level data available from ABSNet for private label loans (purchases only). The model treats competing risks independently, indicating 1 for failure and 0 for censoring. Each coefficient is the effect of the corresponding variable on the log hazard rate for either the default or prepayment of a mortgage. The conditional hazard is captured by performance month dummies, where performance is tracked over the first 60 months of the sample. The sample is truncated at December 2004 for columns (1) and (2), and at June 2007 for columns (3) and (4). Errors are clustered at CBSA level.

	(1) default	(2) prepayment
log(FICO)	-2.481***	0.448***
	(0.064)	(0.018)
owner occupied	0.025*	0.372***
	(0.014)	(0.005)
original r - original 10 year rate	0.429***	-0.011***
	(0.004)	(0.001)
log(original amount)	0.137***	0.324***
	(0.01)	(0.003)
log(original LTV)	0.572***	0.183***
	(0.012)	(0.005)
adjustable rate mortgage	0.487***	0.579***
	(0.016)	(0.004)
log(Cumulative HPA)	-1.826***	-1.581***
	(0.051)	(0.011)
coupon gap	0.848***	-0.261***
	(0.007)	(0.002)
unemployment	0.080***	0.001
	(0.004)	(0.001)
Asset type: Prime	-0.808***	-2.719***
	(0.044)	(0.014)
Asset type: Second Lien	-0.794***	0.298***
	(0.038)	(0.011)
Asset type: Subprime	0.402***	1.079***
	(0.025)	(0.005)
CBSA FE	N	N
Month since origination FE	N	Y
Observations	2,630,290	76,374,400

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1..12: This table shows estimates using the maximum likelihood estimation of a complementary log-log specification, using a hazard specification for prepayments and a dummy indicator for default, on the loan level data available from ABSNet for private label loans (purchases only). The hazard model treats default risk as censored. Each coefficient is the effect of the corresponding variable on the log hazard rate for prepayment or the log probability of default of a mortgage. The conditional hazard is captured by performance month dummies, where performance is tracked over the first 60 months of the sample. The sample is truncated at December 2004.

	default indicator (by the end of the given year)									
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
log(FICO)	-2.485***	-3.599***	-4.816***	-2.583***	-3.141***	-3.682***	-4.561***	-4.160***	-3.029***	-2.059***
	(0.494)	(0.257)	(0.151)	(0.101)	(0.071)	(0.052)	(0.038)	(0.027)	(0.018)	(0.014)
owner occupied	-0.318**	0.037	0.263***	0.133***	-0.214***	-0.329***	-0.333***	-0.247***	-0.097***	-0.148***
	(0.139)	(0.069)	(0.041)	(0.024)	(0.016)	(0.011)	(0.008)	(0.006)	(0.004)	(0.003)
original r - original	-0.052	0.277***	0.199***	0.431***	0.459***	0.343***	0.164***	0.178***	0.158***	0.102***
10 year rate	(0.038)	(0.018)	(0.011)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
log(original amount)	-0.053	-0.038	-0.235***	0.125***	0.150***	-0.026***	-0.297***	-0.126***	-0.029***	-0.013***
	(0.084)	(0.043)	(0.025)	(0.016)	(0.011)	(0.007)	(0.005)	(0.003)	(0.002)	(0.002)
log(original LTV)	0.828***	0.698***	0.585***	0.772***	0.682***	0.548***	0.445***	0.178***	0.124***	0.078***
	(0.266)	(0.099)	(0.030)	(0.019)	(0.014)	(0.010)	(0.007)	(0.004)	(0.003)	(0.002)
adjustable rate	-0.707***	0.145**	0.305***	0.335***	0.261***	0.269***	0.291***	-0.045***	-0.130***	0.001
mortgage	(0.104)	(0.058)	(0.035)	(0.023)	(0.016)	(0.011)	(0.008)	(0.006)	(0.004)	(0.003)
log(cumulative HPA)	1.921***	2.981***	4.548***	-3.303***	-1.878***	-0.877***	0.412***	-1.998***	-5.796***	-4.319***
	(0.676)	(0.248)	(0.122)	(0.103)	(0.054)	(0.030)	(0.018)	(0.017)	(0.011)	(0.007)
coupon gap	-1.930***	0.216***	-0.591***	1.234***	0.998***	0.832***	0.170***	-1.057***	-0.810***	0.889***
	(0.062)	(0.037)	(0.019)	(0.013)	(0.009)	(0.006)	(0.005)	(0.004)	(0.002)	(0.002)
unemployment	0.137***	-1.052***	-0.342***	-0.080***	0.011**	0.126***	0.176***	0.004***	-0.183***	-0.309***
	(0.037)	(0.026)	(0.014)	(0.009)	(0.006)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Asset type: Prime	0.000	-1.048***	-0.805***	-0.748***	-0.621***	-0.299***	-0.248***	-0.669***	-1.456***	-1.640***
	(.)	(0.245)	(0.100)	(0.068)	(0.049)	(0.035)	(0.028)	(0.024)	(0.018)	(0.011)
Asset type: Second Lien	0.000	-3.509***	-5.936***	-4.410***	-1.984***	-0.213***	0.471***	0.877***	0.639***	0.616***
	(.)	(1.012)	(1.002)	(0.271)	(0.062)	(0.027)	(0.018)	(0.012)	(0.007)	(0.005)
Asset type: Subprime	2.872***	0.939***	0.213***	0.147***	0.274***	0.438***	0.742***	1.027***	0.777***	0.710***
	(0.311)	(0.128)	(0.062)	(0.040)	(0.028)	(0.019)	(0.014)	(0.010)	(0.005)	(0.004)
Obs	230,631	516,866	865,545	1,435,035	2,630,290	4,307,739	5,766,680	6,014,866	6,014,866	6,014,866

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1..13: This table shows estimates using the maximum likelihood estimation of a complementary log-log specification, using a dummy indicator for default, on the loan level data available from ABSNet for private label loans (purchases only). For each year, variables are taken at the measurement point (either default time, if defaulted, or observation time, which is the end of the given year).

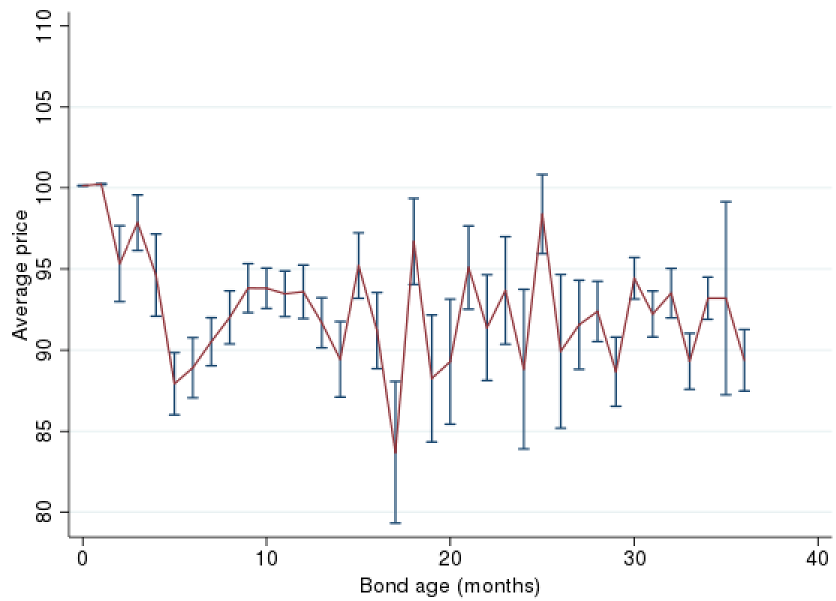


Figure 1..2: Average tranche price by age of the bond in months. For our sample of bonds originated in 2004 and 2005 we compute the average price by the time elapsed (in months) since the bond issue. Vertical whiskers show the standard errors.

	(1)	(2)	(3)	(4)
	AAA balance at origination as share of deal issuance			
Opacity index	-0.104***	-0.0835***	-0.101***	-0.0259*
	(0.0154)	(0.0153)	(0.0151)	(0.0151)
Observations	1,902	1,902	1,902	1,902
Model-implied PD	N	Y	Y	Y
Vintage year	N	N	Y	Y
Asset type	N	N	N	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..14: Regression results from running a linear regression at deal level of AAA origination (as share of total) on the deal opacity index. Controls include model-implied PD, vintage year (we include vintages up to June 2005) and asset type.

	downgrade		
	(1)	(2)	(3)
	All	AAA only	Non-AAA only
Deal average correlation	0.211		
	(0.189)		
Average correlation within rating bucket		0.721*	0.369*
		(0.427)	(0.217)
Price	-0.0185***	-0.0446***	-0.00937***
	(0.00152)	(0.00305)	(0.00150)
Coupon	-0.123***	-0.0402	-0.183***
	(0.0178)	(0.0245)	(0.0240)
Subordination	-3.168***	-4.144***	-4.113***
	(0.271)	(0.601)	(0.316)
Observations	26,242	14,034	12,206
Rating at first transaction	Y	N	Y
Vintage year	Y	Y	Y
Asset type	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1..15: Regression results from running logit regression 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default, as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Column (1) includes all issues; columns (2) and (3) split the sample between bonds rated AAA at origination and the rest, respectively. Independent variables include deal level average correlation (column 1), AAA average correlation (column 2), sub-AAA average correlation (column 3) and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Errors are clustered at deal level.

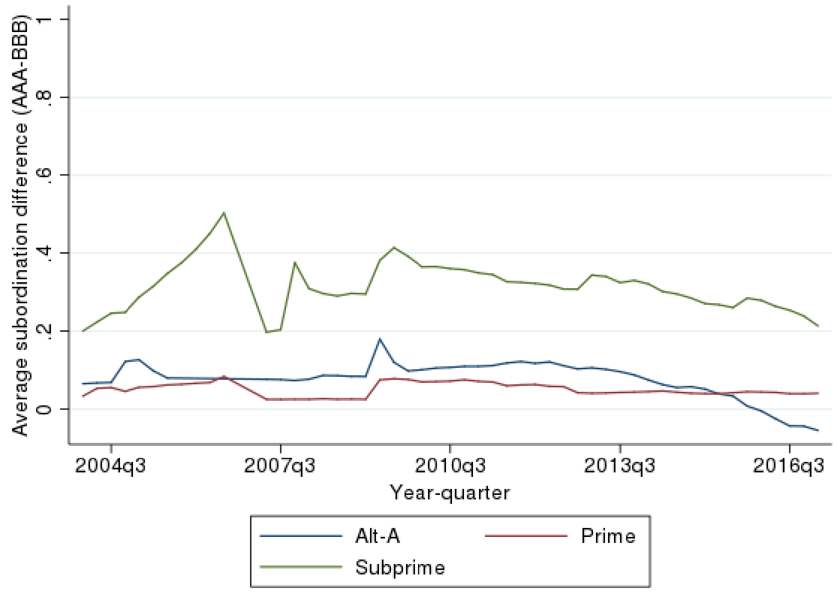


Figure 1..3: Average subordination difference between AAA and BBB bonds. Source: ABSNet bond data.The figure presents the difference between the average AAA and average BBB subordination over trading time (for early vintages, prior to June 2005) using the rating at the given trading time. The difference is computed by asset type.

removing Interest Only, Principal Only, Inverse Floater and Fixed to Variable bonds from the sample.

Notice that the most aggressive cleaning step is the removal of observations where price is missing. As dicussed in subsection 1.2, this is due to the data gap that covers late (2005 and more recent) vintages.

Loan level data

We start with a set of 22,008,610 loan originations. Of our originations set, 21,759,836 map to one of our deal IDs. Below is a summary of deal level averages of certain covariates (FICO score, LTV, private mortgage insurance coverage percentage) are computed.[22]

Historic data are contained in monthly reports. From the input 21,996,382 facilities we have at least one observation for 17,350,072 of them. We recover a total 792,664,139 loan-month observations from payment history (on average 45.7 obs per loan). From there we can compute default rates at deal level. We have loss event data for 3,986,974 observations, linked to 5,965 deal IDs. From there we can compute LGDs at deal level or vintage level.

[22]Simple averages were preferred over weighted averages (weighted by e.g. the initial securitized balance) as this reduces the number of missing observations.

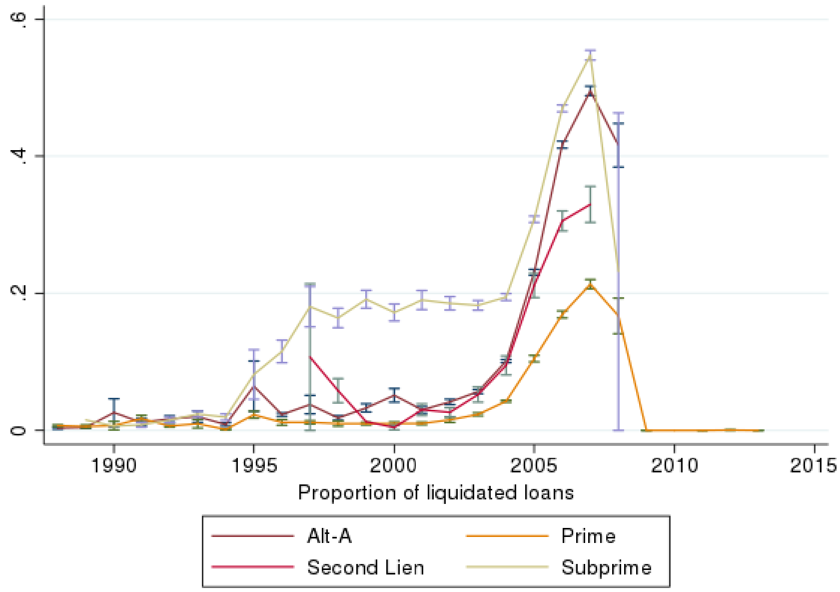


Figure 1..4: Probability of default by vintage year. We compute the default rate for each of the deals that compose our population, and then average by vintage year and asset type. The results are presented here along with standard error bands around the average.

At the loan level, we keep only loans having purchase as purpose. This reduces the sample to 8,862,561 loans. Aside minor cleaning (originations before 1980, errors in time stamps) we arrive to 7,145,251. From these we discard asset types other than Alt-A, Prime, Second Lien or Subprime to arrive at the initial sample composed of early and late vintages.

Variations on the baseline model

Pricing results with constant default probability and prepayment speed

In this section we use a constant PD, by asset type, given as the

After the collapse of private label securitization in 2007, most securitization conduits are insured against default risk by the Government-Sponsored Entities (Fannie Mae and Freddie Mac), making prepayment risk the most significant one in the literature. Schwartz and Torous, 1989 and Stanton, 1995 measure the value of prepayment option in default-free securities (guaranteed by the Government-Sponsored Entities). Downing, Stanton, and Wallace, 2005 propose a two-factor valuation model that distinguishes the separate, competing risks carried by the default and the prepayment options. Sugimura, 2004 develops an intensity model to price RMBS (pass-through) bonds not insured against default risk, and thus exposed to both prepayment and default risk (but credit events in his approach are assumed

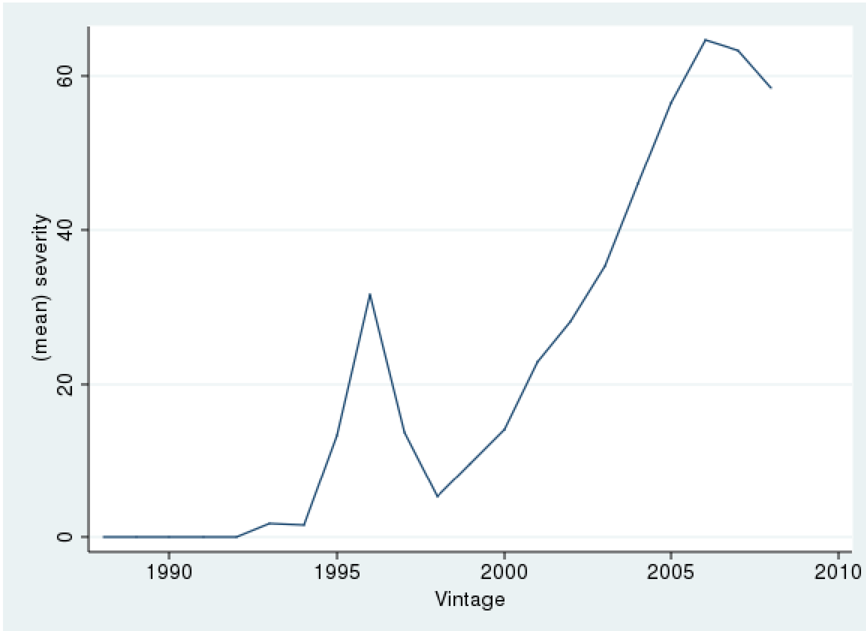


Figure 1..5: Percentage loss given default by vintage year. The aggregate loss given default is computed from the sample of loans associated to the deals that compose our population of CMOs.

to be uncorrelated). We seek an accurate measure of prepayment while keeping the focus on default risk, hence the choice of the PSA schedule (see Figure 1..7).

In order to chose the PSA factor we look at the class balance. Class balance factor, which measures balance over time relative to the tranche initial balance, reflects both losses and prepayments, thus is an upper bound for prepayments. The results in Figure 1..6 suggest that 150% is an appropriate upper bound. Gorton, 2009 states that subprime deals were mostly linked to ARMs (see Figure 1..10), those being a priori subject to higher prepayment rates.[23] The evolution of class factor over time does not suggest a radically different prepayment rate for subprime deals in our sample. In this section we will apply the PSA schedule, with a factor of 150%, to all tranches within the same deal.

Cornaggia, Cornaggia, and Hund, 2017 find that ratings are not comparable across broad asset types (corporate, CDO, ABS and RMBS). Within RMBS we emphasize the difference across asset types (prime, subprime and Alt-A), and in this section document a difference in information across asset types, namely between Alt-A and other types.

Breaking the change by asset type we see an increase for Alt-A tranches (from 0.36 to 0.40), no change for prime ones (0.30) and a decrease for subprime deals (from 0.59 to 0.49,

[23]He finds that the shift to subprime deals happened for the later cohorts. Similarly, we find that later cohorts see faster reductions in balance.

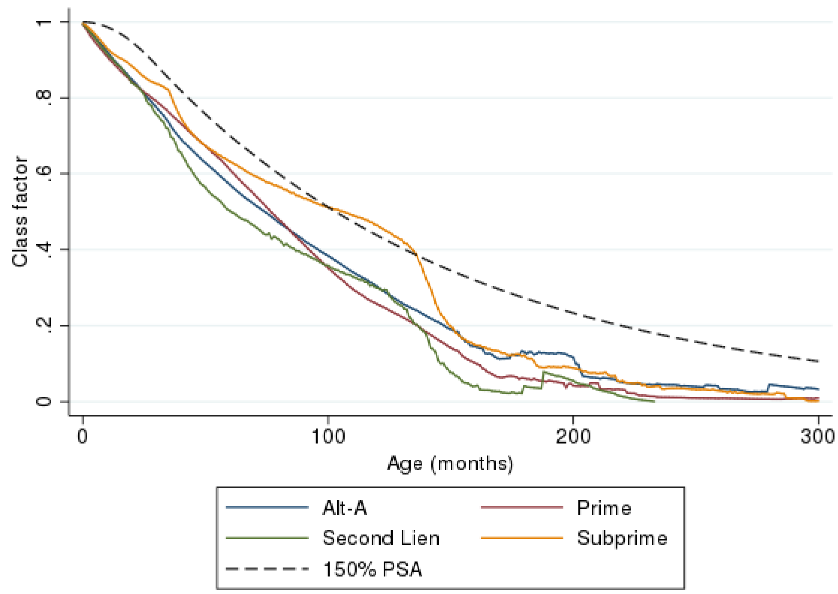


Figure 1..6: Average class balance factor by asset class over tranche age. Alongside the averages, we compute the balance factor that results from a 150% payment schedule alone (excluding planned amortization).

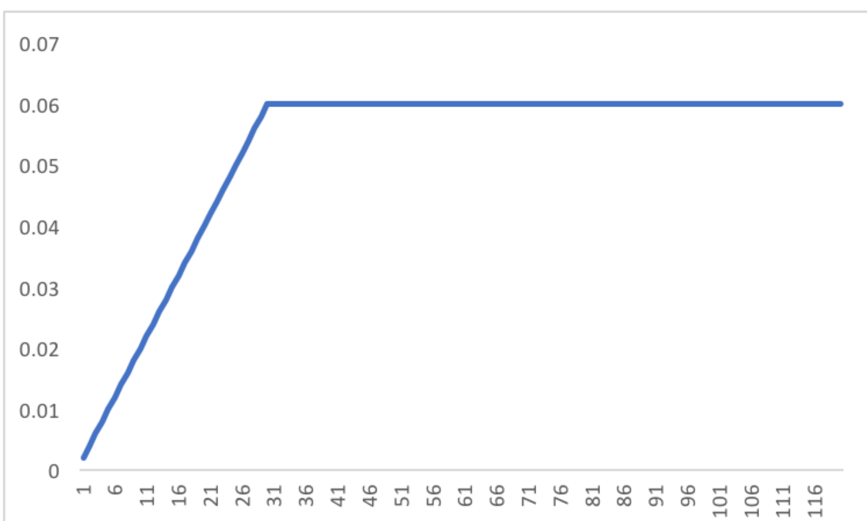


Figure 1..7: Standard Prepayment Model of The Bond Market Association. Prepayment percentage for each month in the life of the underlying mortgages, expressed on an annualized basis.

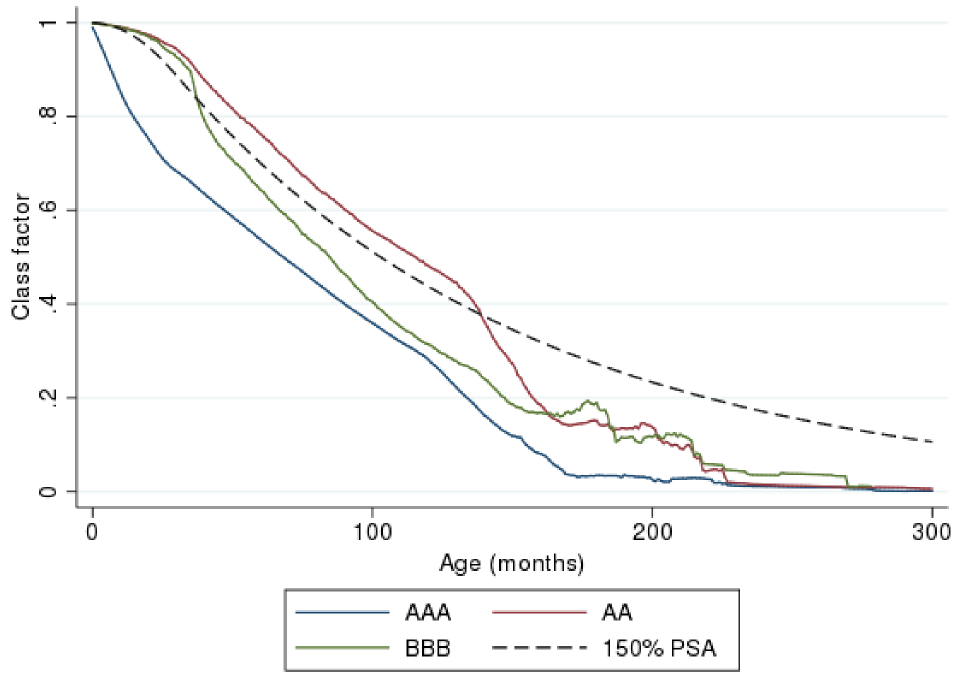


Figure 1..8: Plot of average class factor against tranche age by tranche initial rating.

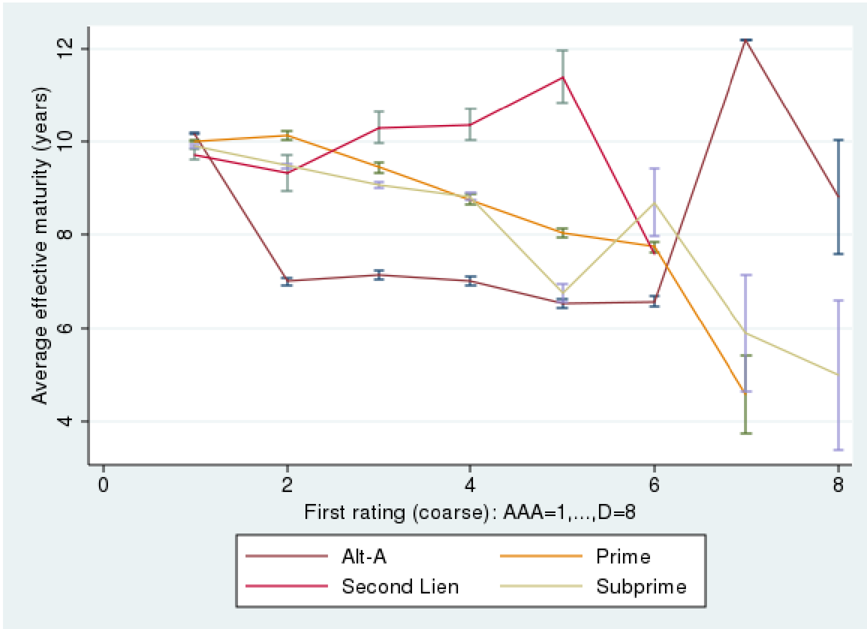
significant at 99%) so that the upward adjustment during seems to have mainly affected Alt-A issues.

In terms of seniorities, the difference observed by Buzková and Teplỳ, 2012 over the crisis is mainly driven by mezzanine tranches (7%-10% and 10%-15%). Figure 1..17 also suggests the increase in correlations is larger among intermediate seniorities, though not as large as the one they observe on the CDX tranches.

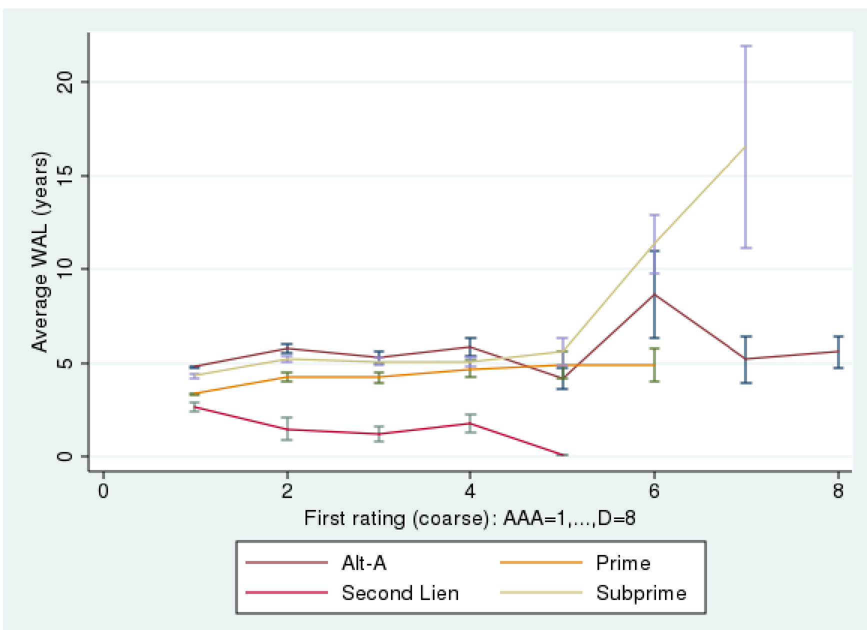
The regression results on price informativeness are similar to those obtained in Section 1.4: implied default correlations are informative when they are linked to well-documented deals, which happens both for AAA and non-AAA tranches. First, the results in Table 1..22 confirm those of Table 1.4 in that implied correlations are informative about bond downgrades, except for AAA tranches. Second, the split by opacity index (see Table 1..24) yields a similar results to that in Table 1.5. Finally, the further split by rating in Table 1..24 yields results that are consistent with those in Table 1.5.

The information content of news in prices

Using the partial observations we recover from the ABSNet data (namely, observations post June 2009) we study the effect of news in prices across the cycle. A number of cleaning stages (see Table 1..19 in the appendix) are applied to attain the final sample, which contains



(a) Average realized



(b) WAL

Figure 1..9: Average realized and weighted average life by coarse rating and asset type. The second panel includes observations where we found a matching WAL in Bloomberg.

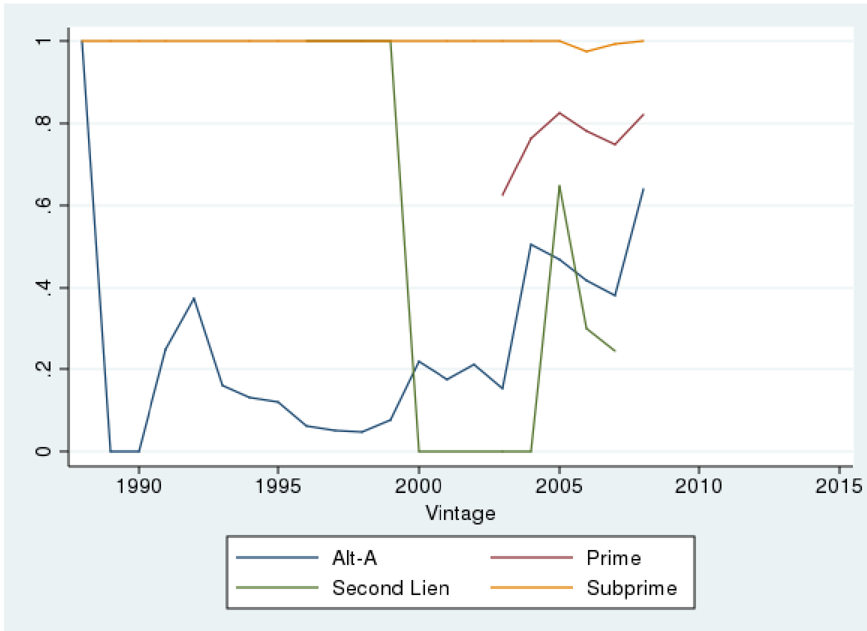


Figure 1..10: Proportion of ARM loans by vintage and asset type.

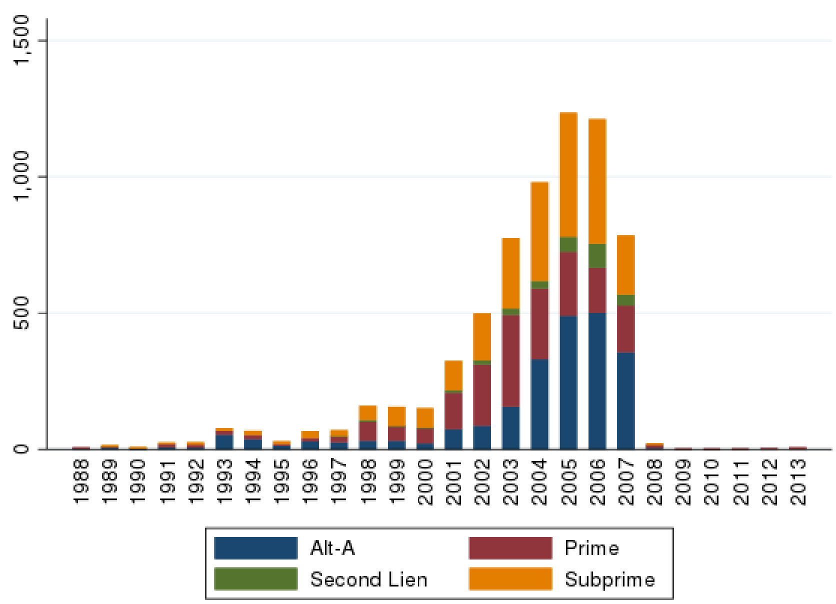


Figure 1..11: Number of deals originated by asset type and vintage year.

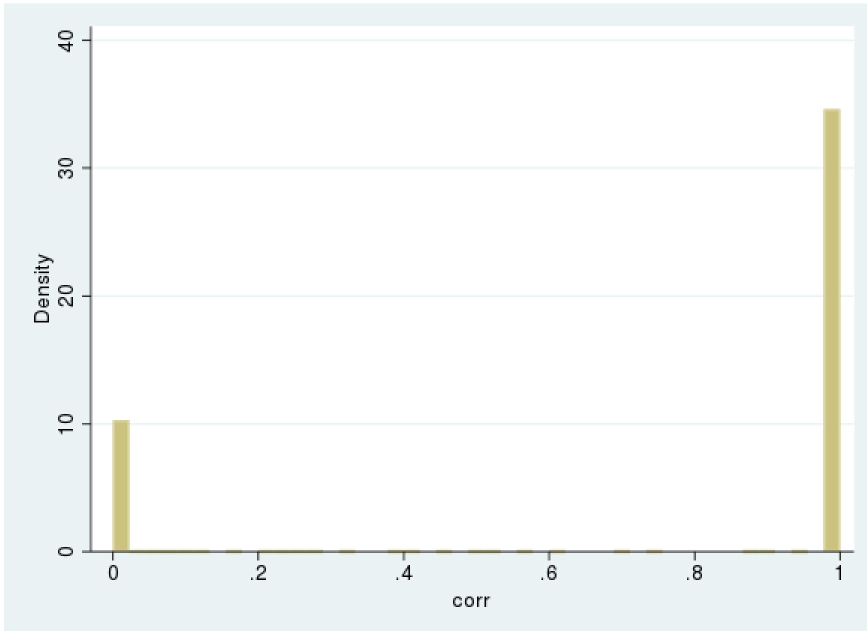


Figure 1..12: Histogram plotting all outcomes from the pricing model.

6,322,690 panel observations -close to 64 transactions per tranche-. We illustrate the overall numbers in Figure 1..18.

The results up to now suggest implied correlation at origination is predictive of downgrades to the extent that the loans have full documentation. Having seen the role of initial signals, our next question is about the role of price news both from rating agencies and the market. While initial ratings rely on an a priori assessment, its evolution over time reflects progressively more of the bond performance, implying that updated rating values should in principle absorb the information that was initially private. We estimate panel 1.13 using a linear model, with random effects in order to control for tranche-invariants such as first rating and first implied correlation. The advantage of the panel specification 1.13 is that we can incorporate the partial information coming from the late vintages (after June 2005).

$$outcome_{it} = \alpha_{it} + \beta_0 \rho_{i,0} + \eta_0 rating_{i0} + \beta_1 \rho_{i,t-1} + \eta_1 rating_{i,t-1} + \gamma X_{i,t} + \varepsilon_{it}. \qquad (1.13)$$

In equation 1.13 $outcome_{it}$ is the month-on-month rating change in notches. Table 1..26 shows that updates in signals contain information about future bond performance, but the signal is not statistically sufficient for prices. This suggests that investors retain private information over the life of the bond, besides the information given by agency ratings. The second finding is that Alt-A investors do not learn over the life of the bond, so that news in ratings remain statistically sufficient for news in correlation in terms of bond performance.

To see the effect of the crisis on the information content of prices, we will use interactions with an indicator dummy for post-2007 transaction to split estimates between before and

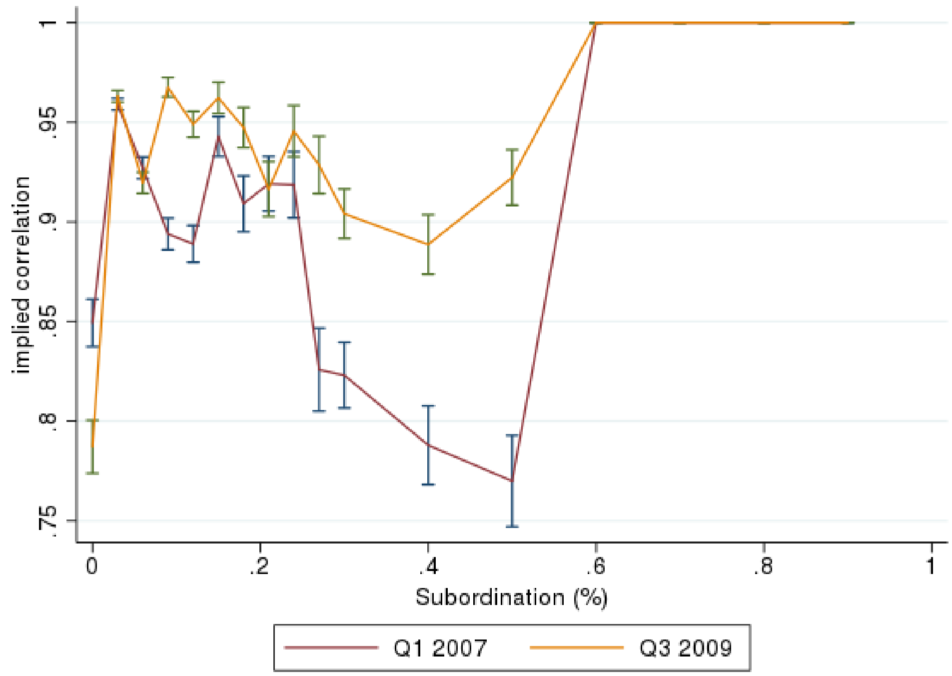
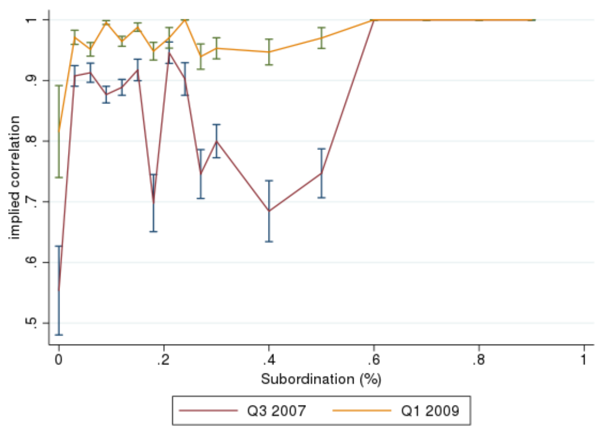


Figure 1..13: Average correlation plotted against tranche subordination percentage, on two given dates. We use the sample of early vintage bonds (originated prior to June 2005). Subordinations are assigned to 10 equally spaced bins. Within each subordination bin we plot the average correlation, along with vertical whiskers representing the standard error of the average.

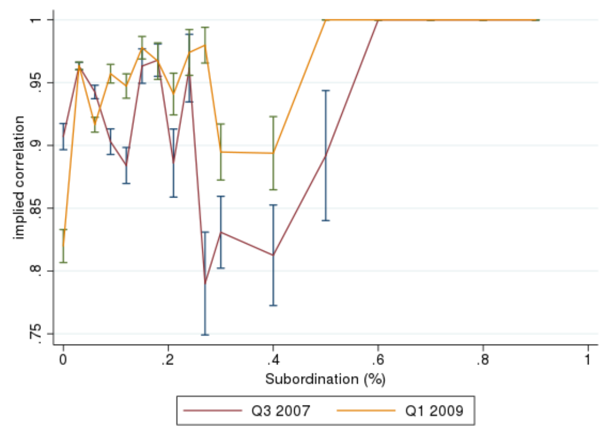
after the crisis. The regression specification is the following:

$$\Delta rating_{it} = \alpha_{it} + \beta_0 \rho_{i,0} + \eta_0 rating_{i0} + 1_{post-07} \tag{1.14}$$
$$+\beta_1 \rho_{i,t-1} \times 1_{post-07} + \eta_1 rating_{i,t-1} \times 1_{post-07} + \gamma X_{i,t} + \varepsilon_{it} \tag{1.15}$$

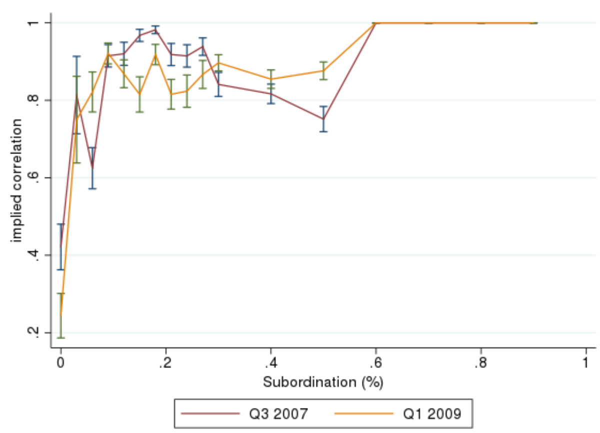
Table 1..27 presents the results of estimating equation (1.15). It shows that most of the effect of news about default correlation shown in Table 1..26 comes from the post-crisis period. Griffin and Nickerson, 2016 discuss how rating agencies improved their methodologies following the crisis. Under such improvement, the expectation would be that ratings become sufficient for implied correlations, but this is not what we observe. An improvement in rating methodology is consistent with more statistical information coming from prices if ratings are now following the market more closely. In that case changes in implied correlation have more statistical power to predict future downgrades by construction of the downgrade process. The other possibility is that investors learned more from the crisis than the rating agencies, but if this is so it is rational for ratings to follow the market more closely.



(a) Alt-A

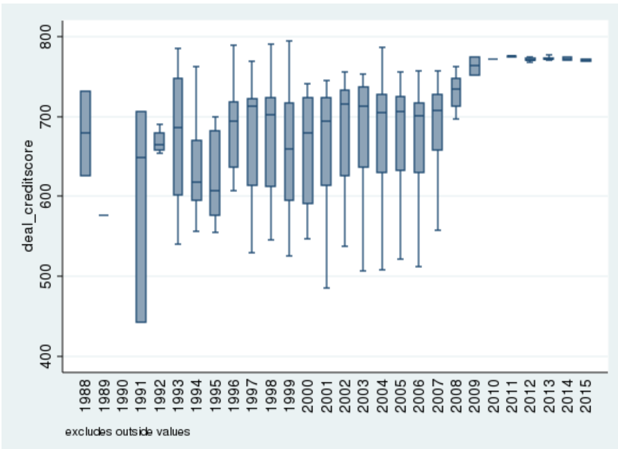


(b) Prime

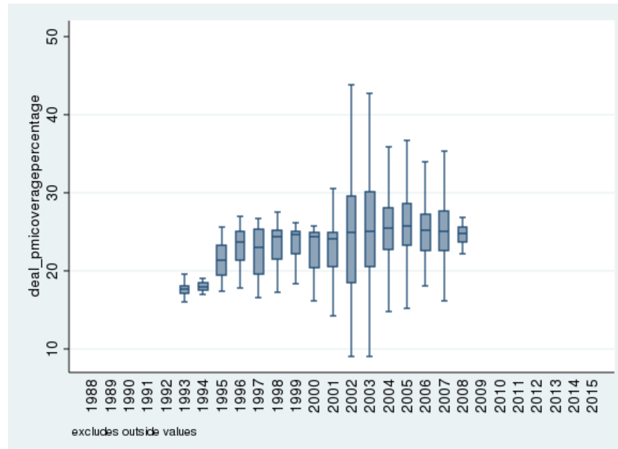


(c) Subprime

Figure 1..14: Average correlation plotted against tranche subordination percentage, on two given dates. Subordination values are assigned to 10 equally spaced bins. Within each subordination bin we plot the average correlation, along with vertical whiskers representing the standard error of the average.

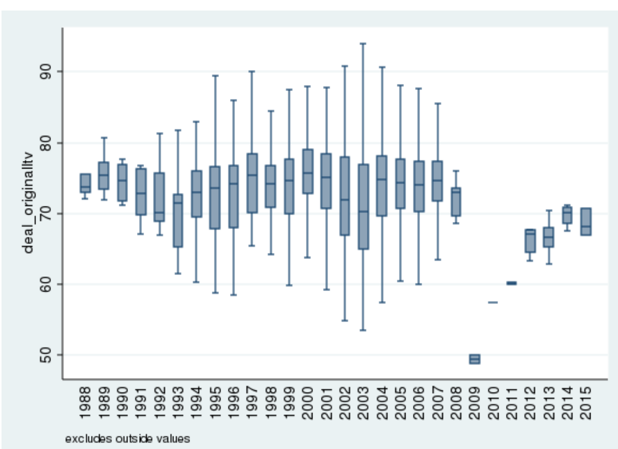


(a) FICO score

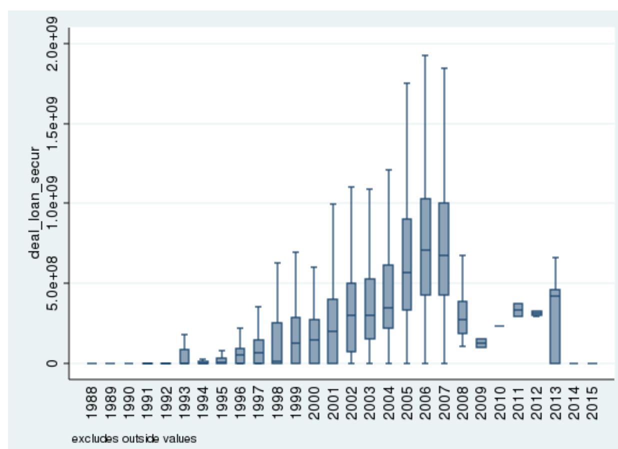


(b) PMI coverage

Figure 1..15: Distribution of covariates over time (vintage year).



(a) LTV



(b) Original securitized balance

Figure 1..16: Distribution of covariates over time (vintage year).

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator			
Deal average correlation	-0.581	-0.155	-0.0162	0.901**
	(0.750)	(0.522)	(0.367)	(0.395)
Price	-0.0165***	-0.0202***	-0.0110***	-0.0167***
	(0.00631)	(0.00343)	(0.00269)	(0.00356)
Coupon	-0.134**	-0.0369	-0.117***	-0.0749
	(0.0649)	(0.0310)	(0.0442)	(0.0465)
Subordination	-0.0512	-1.869***	-4.013***	-5.858***
	(0.852)	(0.653)	(0.489)	(0.959)
Observations	2,489	5,513	7,073	5,049
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..16: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include deal level average implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the value of the documentation index corresponding to the given deal. Errors are clustered at deal level.

In DeMarzo, 2005, two factors drive the benefits and drawbacks of securitization: private information by the issuer, on one hand, and asset correlation, on the other. Like CDOs, CMOs are a priori affected by it.[24] Our measure of beliefs about default correlation reflects in part adverse selection concerns on the part of the investors. Because we can't disentangle these two components empirically, our implied correlation measure is a proxy for market conservatism vis-à-vis information asymmetry. In line with this, Alt-A deals being more reliant on ratings (not only for the first transaction, but also for subsequent ones) potentially reflects a concern for asymmetric information as in Adelino, Gerardi, and Hartman-Glaser, 2016.

[24]Beltran, Cordell, and Thomas, 2017 show that, under asymmetric information, even a modest percentage of bad securities can push security prices far below fundamentals -even to a market meltdown-.

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator - AAA only			
AAA average correlation	5.310	0.701	1.074	3.019***
	(3.508)	(1.594)	(0.962)	(0.857)
Price	-0.0309***	-0.0351***	-0.0328***	-0.0535***
	(0.00991)	(0.00542)	(0.00655)	(0.0118)
Coupon	0.0452***	0.0544	0.0898	0.149**
	(0.0173)	(0.0453)	(0.0580)	(0.0726)
Subordination	0.610	-2.791**	-2.283	-11.79***
	(1.530)	(1.260)	(1.851)	(4.377)
Observations	1,325	3,073	3,272	2,926
Rating at first transaction	N	N	N	N
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y
	Downgrade indicator - not AAA			
Below-AAA average correlation	-1.266	0.527	-0.0727	0.195
	(0.886)	(0.548)	(0.431)	(0.574)
Price	-0.0154**	-0.0127***	-0.00783***	-0.0115***
	(0.00704)	(0.00370)	(0.00249)	(0.00362)
Coupon	-0.357***	-0.174***	-0.201***	-0.155***
	(0.103)	(0.0496)	(0.0529)	(0.0599)
Subordination	0.133	-2.715***	-4.482***	-4.278***
	(1.905)	(0.878)	(0.541)	(0.852)
Observations	1,038	2,248	3,757	2,111
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..17: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year (vintages up to June 2005) and model-implied probability of default as estimated in subsection 1.3. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include AAA average correlation (upper panel), sub-AAA average correlation (lower panel) and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the value of the documentation index corresponding to the given deal. Errors are clustered at deal level.

	(1)	(2)	(3)	(4)
	AAA balance at origination as share of deal issuance			
Opacity index	-0.104***	-0.0835***	-0.101***	-0.0259*
	(0.0154)	(0.0153)	(0.0151)	(0.0151)
Observations	1,902	1,902	1,902	1,902
Model-implied PD	N	Y	Y	Y
Vintage year	N	N	Y	Y
Asset type	N	N	N	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..18: Regression results from running a linear regression at deal level of AAA origination (as share of total) on the deal opacity index. Controls include model-implied PD, vintage year (we include vintages up to June 2005) and asset type.

Stage	Tranches left
Remove deals that are entirely made of mixed asset types	119,215
Remove deals where one tranche has subordination >1	119,215
Remove observations with missing price	74,307
Remove mixed-type asset pools	74,253
Remove PO, IO, IF and FtV	71,950

Table 1..19: Data cleaning stages with number of tranches outstanding at the end of each step.

Additional causes of default clustering: frailty and contagion

Following Azizpour, Giesecke, and Schwenkler, 2016, defaults are driven by three factors: systemic risk[25] as captured by macroeconomic variables (Bullard, Neely, and Wheelock, 2009; Khandani, Lo, and Merton, 2013)[26], an unobserved frailty factor (Duffie et al., 2009;

[25] Bisias et al. (2012) provides a survey of systemic risk measures. See also Chan-Lau et al. (2009). Other approaches include macro measures (costly asset-price boom/bust cycles, property-price, equity-price, credit-gap indicators), forward-looking measures (e.g. absorption rate as in Kritzman et al. (2010)), cross-subsectional measures (CoVaR, Co-Risk, marginal and systemic expected shortfall, see Acharya et al. (2012)), stress tests (e.g. Duffie (2011)), illiquidity and insolvency (e.g. Brunnermeier, Gorton, and Krishnamurthy (2011)). Giglio et al. (2013) use predictive quantile regression to provide an empirical assessment of 17 of them. Their main finding is that, overall, the compendium of systemic risk measures contains useful predictive information. Instead individual measures tend to fail in capturing systematic risk.

[26] The characterization of systemic risk as deterioration of macroeconomic indicators leaves aside the widely discussed view that the pre-crisis mortgage system was systemically vulnerable (Hellwig, 2009; Poitras and Zanotti, 2016).

S&P rating	Code	Coarse rating	Code
AAA	1	AAA	1
AA+	2	AA	2
AA	3	AA	2
AA-	4	AA	2
A+	5	A	3
A	6	A	3
A-	7	A	3
BBB+	8	BBB	4
BBB	9	BBB	4
BBB-	10	BBB	4
BB+	11	BB	5
BB	12	BB	5
BB-	13	BB	5
B+	14	B	6
B	15	B	6
B-	16	B	6
CCC	17	C	7
CCC-	18	C	7
CC	19	C	7
C	20	C	7
D	21	D	8
NR	-	NR	-

Table 1..20: Mapping of ratings - fine and coarse level (with numbering code)

	(1)	(2)	(3)
Asset type	Early vintages	Late vintages	Model PD
Alt-A	7.5%	19.5%	24.5%
Prime	2.3%	6.6%	6.4%
Second Lien	7.2%	25.8%	21.1%
Subprime	14.8%	30.5%	30%
Observations	4,060,698	631,793	2,112

Table 1..21: Liquidation rates from the loan sample, and PD used for baseline estimation. Column (1) calculates the percentage of loans linked to early vintage deals (before June 2005) that are liquidated. Column (2) calculates the same ratio for late vintage loans. Column (3) shows the PD parameters used for the pricing model, calculated as the average of the deal level liquidation rates for both early and late deals.

	downgrade		
	(1)	(2)	(3)
	All	AAA only	Non-AAA only
Correlation at first transaction	0.248***	0.0378	0.138**
	(0.0531)	(0.114)	(0.0561)
Observations	29,938	17,234	12,702
Rating at first transaction	Y	N	Y
Vintage year	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1..22: Regression results from running logit regression 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Column (1) includes all issues; columns (2) and (3) split the sample between bonds rated AAA at origination and the rest, respectively. Errors are clustered at deal level.

	(1)	(2)	(3)	(4)
	Alt-A	Prime	Second Lien	Subprime
	Downgrade indicator			
Correlation at first transaction	0.198*	0.293**	-0.907	0.266***
	(0.101)	(0.130)	(0.910)	(0.0693)
Observations	8,766	11,862	60	8,620
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..23: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to a given asset type. Errors are clustered at deal level.

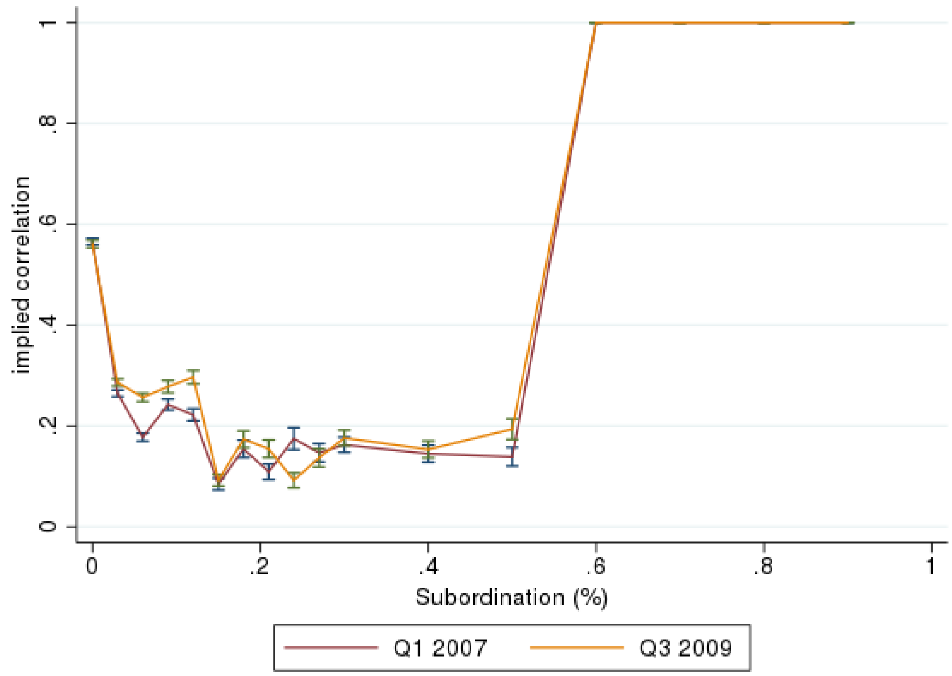


Figure 1..17: Average correlation plotted against tranche subordination percentage, on two given dates. We use the sample of early vintage bonds (originated prior to June 2005). Subordinations are assigned to 10 equally spaced bins. Within each subordination bin we plot the average correlation, along with vertical whiskers representing the standard error of the average.

Kau, Keenan, and Li, 2011) and a contagion factor, which captures the extent to which more defaults increase the conditional intensity of default arrival.

A given loan n has a default time T_n. Defaults have a conditional mean of arrival λ given by

$$\lambda_t = \exp\left(a_0 + \sum_{i=1}^{d} a_i X_{i,t}\right) + Y_t + Z_t$$

where X represents a vector of macroeconomic variables. Unobservable frailty Z_t follows the CIR process

$$dZ_t = k(z - Z_t)dt + \sigma\sqrt{Z_t}dW_t$$
$$Z_0 \sim \Gamma\left(\frac{2kz}{\sigma^2}, \frac{\sigma^2}{2k}\right)$$

	(1) [0, 0.25)	(2) [0.25, 0.5)	(3) [0.5, 0.75)	(4) [0.75, 1]
		Downgrade indicator		
Correlation at first transaction	-0.142	0.237^{**}	0.357^{***}	0.281^{**}
	(0.203)	(0.105)	(0.0871)	(0.130)
Observations	3,149	7,274	8,824	7,096
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..24: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the average documentation index corresponding to the given deal. Errors are clustered at deal level.

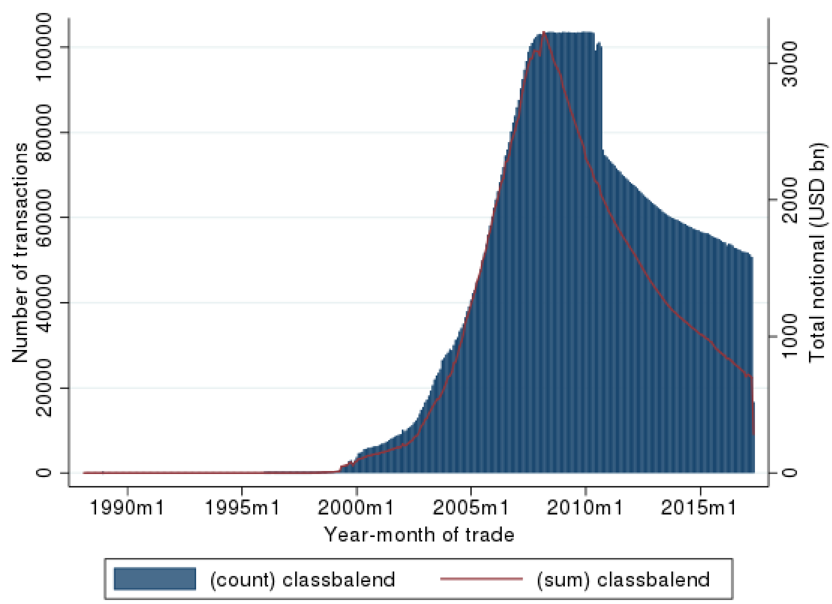


Figure 1..18: Tranche balance and number of bonds outstanding by transaction year and month.

	(1)	(2)	(3)	(4)
	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]
	Downgrade indicator - AAA only			
Correlation at first transaction	-0.539	-0.0777	0.378*	0.595**
	(0.356)	(0.168)	(0.210)	(0.297)
Observations	1,760	4,544	4,538	4,369
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y
	Downgrade indicator - not AAA			
Correlation at first transaction	-0.147	0.106	0.221**	0.0974
	(0.271)	(0.126)	(0.0908)	(0.138)
Observations	1,204	2,704	4,222	2,701
Rating at first transaction	Y	Y	Y	Y
Vintage year	Y	Y	Y	Y
Asset type	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..25: Regression results from running logit specification 1.12 by maximum likelihood, controlling for vintage year, for vintages up to June 2005. The dependent variable is a dummy indicator for whether there was a downgrade by December 2009. Independent variables include implied correlation and coarse rating dummy indicator at the time of the first transaction. The dependent variable is the downgrade indicator. Each column presents the results on a subset of the data corresponding to the average documentation index corresponding to the given deal. Errors are clustered at deal level.

Defaults are self-exciting, in the sense that the mass of defaults at a given time increases the rate of arrival. This is captured by means of a contagion factor Y such that

$$Y_t = b \sum_{n:T_n \leq t} e^{-\kappa(t-T_n)} U_n$$

$$U_n = \max(0, \log u_n)$$

where u_n is the sum of defaulted debt at time T_n. This implies that larger defaults are followed by more defaults.

The estimation of $\theta = (a, k, z, \sigma, b, \kappa)$ is a filtered likelihood problem (the likelihood is a posterior mean of the complete-data likelihood), and can be solved following Giesecke and Schwenkler, 2016. The likelihood is written as a product of two terms, one that depends on event data (defaults) and one that depends on factor data. The decomposition is based

	(1) Alt-A	(2) Prime	(3) Second Lien	(4) Subprime
	One-month change in rating (notches)			
Lagged correlation (1 month)	0.004	0.007**	-0.025***	-0.007***
	(0.004)	(0.003)	(0.008)	(0.003)
Lagged rating (1 month)	-0.026***	-0.012***	-0.026***	-0.038***
	(0.001)	(0.001)	(0.003)	(0.001)
Correlation at first transaction	0.003	0.027***	-0.004	0.008***
	(0.005)	(0.003)	(0.008)	(0.003)
Rating at first transaction	0.017***	0.017***	0.001	0.010***
	(0.001)	(0.001)	(0.005)	(0.001)
Subordination	0.084***	0.090***	-0.119***	-0.148***
	(0.022)	(0.019)	(0.019)	(0.008)
Observations	2,032,055	1,773,020	55,293	1,452,760
Vintage	Y	Y	Y	Y
Year-quarter	Y	Y	Y	Y

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..26: Regression results from running the panel regression 1.13, by GLS with tranche random effects. The first line gives the coefficient for the change over 1 month (lagged 1 month) of the correlation coefficient, and the second one the coefficient for the change over 1 month (lagged 1 month) of the change in rating (in notches). Errors are clustered at deal level.

on a change of measure, which resolves the interaction between the point process and the factors of λ.[27] One of the terms is a point process filter, which makes the computation difficult. Giesecke and Schwenkler, 2016 propose an approximation based on a quadrature method, from which the posterior mean can be computed. They write an algorithm and derive conditions for convergence.

[27] An alternative is to apply the expectation maximization (EM) algorithm. Giesecke and Schwenkler, 2016 compare the two approaches.

	(1) Alt-A	(2) Prime	(3) Second Lien	(4) Subprime
		Size of downgrade (notches)		
Lagged correlation	-0.001	-0.018***	0.002	0.005
	(0.005)	(0.004)	(0.017)	(0.003)
Lagged correlation × post-07=1	0.005	0.027***	-0.028	-0.013***
	(0.006)	(0.004)	(0.018)	(0.004)
Lagged rating	-0.055***	-0.095***	-0.082***	-0.026***
	(0.016)	(0.009)	(0.014)	(0.008)
Lagged rating × post-07=1	0.029*	0.083***	0.056***	-0.012
	(0.016)	(0.009)	(0.014)	(0.008)
post-07=1	0.016	-0.076***	-0.013	0.130***
	(0.019)	(0.010)	(0.034)	(0.011)
Correlation at first transaction	0.003	0.028***	-0.001	0.008***
	(0.005)	(0.003)	(0.008)	(0.003)
Rating at first transaction	0.017***	0.017***	0.003	0.009***
	(0.001)	(0.001)	(0.005)	(0.001)
Subordination	0.084***	0.089***	-0.120***	-0.148***
	(0.022)	(0.019)	(0.019)	(0.008)
Observations	2,032,055	1,773,020	55,293	1,452,760
Vintage	Y	Y	Y	Y
Year-quarter	Y	Y	Y	Y

Marginal effects; Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1..27: Regression results from running the panel regression 1.13, by GLS with tranche random effects. The first line gives the coefficient for the change over 1 month (lagged 1 month) of the correlation coefficient, and the second one the coefficient for the change over 1 month (lagged 1 month) of the change in rating (in notches). Errors are clustered at deal level.

Chapter 2

Identification of Other-regarding Preferences: Evidence from a Common Pool Resource Game in the Field

2.1 Introduction

Common pool resources (CPR) are held by a collective of individuals. Each of them can extract from the CPR in order to derive an individual payoff. At the heart of a CPR problem lies the danger that individual profit-maximizing behavior leads to depletion of the common pool resource, and hence to a loss of utility for all the agents. The social dilemma that arises from the wedge between the Nash equilibrium (NE) and the social optimum is a key concern for the governance of the commons. The corresponding (positive) question of how agents respond to social dilemmas in real life is key to make inference about the motives of individual behavior.

Consistent deviations from the self-regarding NE have been documented in the empirical literature (Rassenti et al., 2000). The existence of pro-social behavior has been widely documented, suggesting that other-regarding preferences are important influences on economic behavior (Fehr, Gächter, and Kirchsteiger, 1997; Bewley, 1999; Fehr and Schmidt, 1999; Fehr and Gächter, 2000; Sobel, 2005). An individual behaves pro-socially in order to help others -including himself- to achieve a common good. Other-regarding preferences are those concerns for the well-being of others and desires to uphold ethical norms. They reduce social inefficiency in the absence of complete contracts (Arrow, 1971; Becker, 1976; Akerlof, 1984) and thus are key to solve social dilemmas (Ostrom, 1990), in which the uncoordinated actions of individuals result in an outcome that is Pareto inefficient.

Different types of social preferences exist. "Understanding Social Preferences with Simple Tests" find empirical evidence about preferences for altruism (social welfare in their setting), for reciprocity and to a lesser extent for equity. Similarly, Bolton and Ockenfels, 2000 argue for other-regarding preferences in the sense of concern for total welfare. Fehr and Schmidt, 1999 stress inequity aversion as an important type. Since then, structural models of pro-social behavior Falk and Heckman, 2009; Manski, 2011; Andreozzi, Ploner, and Soraperra, 2013 have been used to assess the prevalence of a given type of other-regarding preference.

Other-regarding preferences have been largely studied in the context of public goods games (Isaac and Walker, 1988). Common Pool Resource data have been studied by assuming homogeneous preferences, either with only students (Fischbacher, Gächter, and Fehr, 2001; Kurzban and Houser, 2001; Carpenter et al., 2009; Falk, Fehr, and Fischbacher, 2002) based on Walker, Gardner, and Ostrom, 1990 or only real users (see evidence in forest management by Rustagi, Engel, and Kosfeld, 2010 or Margreiter, Sutter, and Dittrich, 2005; Vélez, Stranlund, and Murphy, 2009). In our dataset, users deviate more from the self-regarding outcome than students (Cárdenas 2004; 2011) which is in line with other empirical findings (Carpenter and Seki, 2010; Molina, 2010; Cárdenas, Mantilla, and Sethi, 2015). Several of these papers explain their findings with the existence of other-regarding preferences but do not explore the role of heterogeneity.

Yet heterogeneity of other-regarding preferences is both a prevalent and a relevant phenomenon ("Understanding Social Preferences with Simple Tests"; Leider et al., 2009; Manski and Neri, 2013; Kurzban and Houser, 2005; Goeree, Holt, and Laury, 2002; Burlando and Guala, 2005). Using a random coefficient model, Polania-Reyes, 2015 identifies altruism, conditional reciprocity and self-regarding types of preferences. Similarly, Vélez, Stranlund, and Murphy, 2009 use a random effects specification to assess the prevalence of other-regarding preferences, finding evidence of preferences for conformity. Rodriguez-Sickert, Guzmán, and Cárdenas, 2008 use a model similar in spirit to derive preferences for self-regarding, altruism and cooperation. They focus on the effect of incentives rather than on type identification, as we do here. Compared to these studies, our contribution lies on type identification, which remains largely unexplored among the empirical literature, and less so within a structural model.

This paper uses a structural approach to examine which types of other-regarding preferences individuals exhibit in a common pool resource environment, in which the CPR is collectively owned or shared (e.g. natural resources, land, software) and foregoing the over-exploitation of the jointly used resource leads to a Pareto superior outcome. Understanding heterogeneity of individual preferences in this environment is the first step to the design of Pareto efficient incentives: we estimate simultaneously the distribution of types proposed by economic theory and the parameters of each type in our sample. Then, we examine determinants of other-regarding preferences as suggested by the empirical literature (Almås et al., 2010).

One recent development towards a structural model with heterogeneous preferences has been the simultaneous estimation of preference parameters and type composition in the sample by means of random coefficients models (Polania-Reyes, 2015) and finite mixture models (Cappelen et al., 2007; Cappelen, Sørensen, and Tungodden, 2010). Finite mixture models have been applied to estimate structural models of fairness (Cappelen et al., 2011;

Cappelen et al., 2013b). To our knowledge this is the first model to identify behavioral types (i.e. we are able to assign to each individual her type) with their preference parameters under heterogeneous other-regarding preferences. To do so we use the latent class model described in Pacifico, 2012, estimated using an expectation maximization (EM) algorithm.

A refinement of finite mixture models, latent class models (Train, 2009) have been used to identify other-regarding preferences (Breffle, Morey, and Thacher, 2011; Morey, Thacher, and Breffle, 2006) has already proven fruitful in Ecological Economics. Varela, Jacobsen, and Soliño, 2014 study the heterogeneity of other-regarding preferences for fire prevention in Europe; they argue for the existence of four types: typical, yea-saying, burnt-worried and against.

We use an experimental design and data collected and analyzed in Cárdenas, 2011. His sample is composed of both students and real users of the CPR and has different CPR environments (water, firewood and fish). First, this allows us to compare cognitive aspects of decision-making across the two populations (see section 2.3), which is a contribution to the aforementioned, lab-based studies. Second, the socioeconomic survey data on the (real CPR user) population allow us to find exogenous type drivers in our structural estimate[1], which provides a source of external validity to our type classification. Eventually, the existence of a rich set of (economic and non economic) incentive schemes will allow us to undertand the effect of different incentives on the behavior of different types.

An alternative to individuals deviating from the self-regarding NE out of concern for others' outcomes or behavior is the incorporation of (foreseeable) errors into the best reply function. This is the principle of QRE - Quantal Response Equilibrium (McKelvey and Palfrey, 1995; Goeree, Holt, and Palfrey, 2016). Close to the concept of QRE, another possible explanation of the consistent deviation from Nash behavior comes from the dynamic aspect of learning. Using the same data we use for the present study, Cárdenas, Mantilla, and Sethi, 2015 argue that students' behavior likely follows a payoff sampling equilibrium (PSE). It is a satisfactory explanation for several features of the distribution of outcomes.

Though QRE has been suggested as a competing explanation to other-regarding preferences, the fact is that they look at different (potentially complementary) mechanisms (Arifovic and Ledyard, 2012): the cognitive one for QRE, and what we call the behavioral one, for other-regarding preferences In particular, it has been shown that QRE cannot account for other-regarding preferences (Ioannou, Qi, and Rustichini, 2012; Hoppe and Schmitz, 2013). Largely due to the fact that it only uses one parameter, it cannot explain the large cross-sectional variation in the data. We compare the predictions from our model to a baseline QRE in order to highlight the trade off between parsimony and goodness of fit across the two specifications.

Burlando and Guala, 2005 discuss the learning process in repeated games and conclude that the 'decay of overcontribution' over time depends critically on the group composition.

[1]Survey data covering sociodemographic (idiosyncratic) factors was gathered for real CPR users but not for students. For this reason types are conditional on individual characteristics only for the real CPR user sample.

Group composition is indeed an important factor, which lends credence to the QRE approach. Empirical findings suggest a negative relationship between group heterogeneity and public goods provision (e.g. Alesina, Baqir, and Easterly, 1999; Miguel and Gugerty, 2005; Vigdor, 2004; Lucas, Oliveira, and Banuri, 2014; Fischbacher and Gächter, 2010; Gächter and Thöni, 2005. In that sense, Arifovic and Ledyard, 2012 combine other-regarding preferences and learning. Subjects have a utility function determined by their own payoff, the average group payoff (altruism, or welfare) and the level of disparity between their own payoff and the group average (envy). We use a similar specification[2].

One main difference between our model and theirs is that in their model, agents only have other-regarding preferences over outcomes and not over intentions, which implies reciprocity arises as an equilibrium behavior and not as a type.[3] Because our empirical estimates allow to identify individual types, our study can assess the empirical soundness of introducing a 'cooperator' type.

Compared to Arifovic and Ledyard, 2012 beliefs in our model are cut off: agents in our model only take into account immediately preceding experience, whereas their model features evolutionary learning. In such setting, the variables are a finite set of remembered strategies for each agent and a corresponding probability distribution; learning happens by experimentation, replication and learning. Now, just as preferences can be heterogeneous so can approaches to learning be. Because our focus is on heterogeneity and we cannot jointly identify heterogeneous other-regarding preferences and (independent) heterogeneous cognitive types, we shut down the learning channel to pin down the preferences one.

The paper is organized as follows. In section 2.2 we introduce the CPR framework for this study. In section 2.4 we introduce the different utility functions of other-regarding preferences and derive the structural equations to be estimated. Section 2.3 lays out our evidence in support of not distinguishing cognitive types. Section 2.5 estimates the latent class model and provides the results. Section 2.6 summarizes and concludes.

2.2 Common Pool Resource framework

Description of the CPR game

The experimental setting is well explained in Cárdenas, 2004, (2011).

Individual i can extract $x_i \in \{1, \ldots, 8\}$ units from the CPR. The individual payoff function is common knowledge and is given by

$$\pi_i = \pi(x_i, x_{-i}) = ax_i - \frac{1}{2}bx_i^2 + \varphi(8n - (x_i + x_{-i})) \tag{2.1}$$

[2] Our specification follows Fehr and Schmidt, 1999 rather than Arifovic and Ledyard, 2012, who nevertheless establish the equivalence between the two formulations.

[3] The model in Vélez, Stranlund, and Murphy, 2009 highlights the difference between playing reciprocally and being a reciprocator type. In their model, reciprocal behavior arises from preferences for conforming to what others are expected to do.

The payoff features direct benefits from extraction $60x_i - \frac{5}{2}x_i^2$, reflecting benefits of extraction and a convex cost of effort. In our setting $a = 60$ and $b = 5$, which locates the cost-reward tipping point above our $x_i \leq 8$ limit. The economic tradeoff stems from the indirect costs of depletion $\varphi(40 - (x_i + x_{-i}))$ following from i's as well as others' extraction level. $\varphi = 20$ makes the depletion externality salient. The Pareto efficient outcome -or social optimum (SO)- maximizes the aggregate payoff of the group

$$(x_1^{SO}, \ldots, x_5^{SO}) = argmax_{(x_1,\ldots,x_5)\in\{1,\ldots,8\}^5} \sum_{i=1}^{5} \pi_i \tag{2.2}$$

The socially optimal extraction $x_i^{SO} = 1$ corresponds to the minimum level possible. Instead the Unique Nash Equilibrium (NE) is given by

$$x_i^{NE} = argmax_{x_i} \pi_i \, \forall \, i \tag{2.3}$$

which gives $x_i^{NE} = e = 8$. The wedge between the Pareto optimum and the Nash equilibrium gives rise to the social dilemma.

Participants play a finitely repeated $(T = 10)$[4] partner matching game. At the beginning of period t individuals decide simultaneously (x_{it}, x_{-it}). At the end of period t, the experimenter announces aggregate extraction $(x_{it} + x_{-it})$ and players are informed about other players' aggregate behavior. That is, i does not know individual extraction by $-i$. She only knows the *average* extraction by $-i$: $\overline{x}_{-it} = \frac{\sum_{j \neq i}^{n-1} x_{jt}}{n-1}$. The lack of detail about individual extractions favors the simplification of learning aspects in order to focus on the identification of preferences.

The composition of the group remains the same during the following T rounds $t = 11, \ldots, 20$. At the beginning of round 11 the experimenter announces (and implements) an incentive. The incentive could be monetary (fine or subsidy) or non-monetary (e.g. communication, affecting reputation or other considerations rather than payoffs).

The subgame perfect Nash equilibrium of the repeated game is the same for all the rounds and is equal to the Nash equilibrium, i.e. the self-regarding outcome. [5]

Game outcome in the field

The final sample is composed of 230 students and 705 real CPR users.[6] The first result to motivate this study is that individuals who consistently play the NE strategy are a small

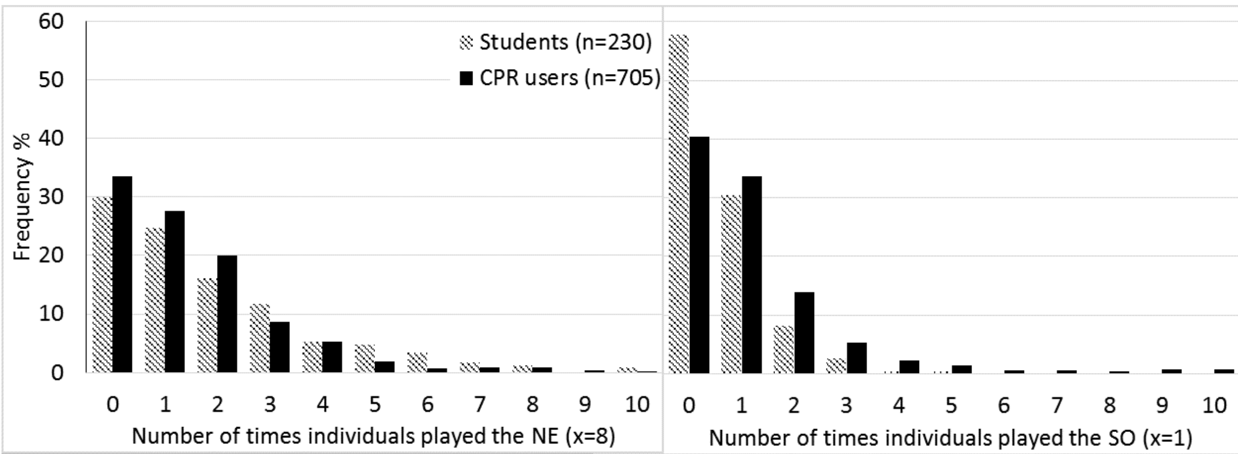
[4]Individuals did not know how many rounds they would play. There were 2 example rounds and 1 practice round and the game started once the experimenter assured the participants understood the procedure.

[5]Individuals might behave pro-socially in the presence of reputation effects (Kreps et al., 1982; Bohnet and Huck, 2004; Mailath and Samuelson, 2006) (see figure 2..2 in the appendix). However, our setting precludes such a reputation channel.

[6]Though the full sample contains 865 real CPR users, some of them ended up participating more than once. Polania-Reyes, 2015 analyses individual behavior of those who played twice.

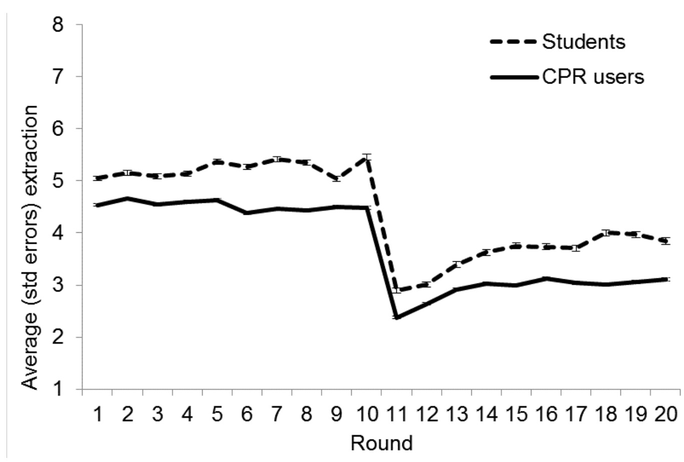
proportion of the sample. Figure 2.2.1 presents how consistently (between 1 and 10 times) individuals extracted 8 units and 1 unit.

Figure 2.2.1: Frequency of participants extracting 8 units (Full extraction) and 1 units (Full cooperation) of the CPR during the baseline rounds.



Besides the natural differences between students and CPR users, we observe a non-uniform distribution of choosing 8 or 1 units. Overall, 33% of the players never played the NE strategy, a quarter of the players chose the NE strategy only once among the ten rounds and 4 of 935 individuals (0.4%)played the NE consistently. In addition, 45% of the player never played the social optimum and only 5 people played such strategy consistently. Figure 2.2.2 shows the path of average extraction.

Figure 2.2.2: Average individual extraction over time



Students extract consistently more than real CPR users (and the difference is significant at 1% in each round). Also students seem more prone to the last-round effect: between rounds 9 and 10 the proportion of the sample extracting 8 units goes from 18% to 28% among students while in the real CPR user sample it remains at 16%.[7] This raises the question of whether students and real CPR users have differing levels of rationality. Following Cárdenas, Mantilla, and Sethi, 2015 we estimate a QRE model and compare the outcome for both samples.

2.3 Static quantal response equilibrium

We estimate a logit QRE specification following Cárdenas, Mantilla, and Sethi, 2015[8] and Goeree, Holt, and Palfrey, 2016 and extend it to the sample of real CPR users. Suppose players make mistakes in choosing their effort decision from $\{1,\ldots,e\}$ but the distribution of those mistakes $P(x=k)$, $k\in\{1,\ldots,e\}$ is common knowledge. If $\pi(x_i,x_{-i})$ is the payoff for x_i given others' pure strategy x_{-i}, let $\pi(x_i,P)$ be the expected payoff of x_i given others' are mixing strategies according to $P(.)$. Then the logistic QRE[9] associated to the mistake parameter $\lambda\in[0,\infty)$[10] is a stable outcome of a belief and choice formation process given by

$$P(x_i=k)=\frac{\exp(\lambda\pi(k,P))}{\sum_{j=1}^{8}\exp(\lambda\pi(j,P))}\;\forall k\in\{1,\ldots,8\} \tag{2.4}$$

λ is chosen to match the QRE distribution, which derived from the payoff function alone, to the observed distribution. Like Cárdenas, Mantilla, and Sethi, 2015 we choose λ in order to minimize mean squared error (MSE). Figure 2.3.1 shows the outcome:

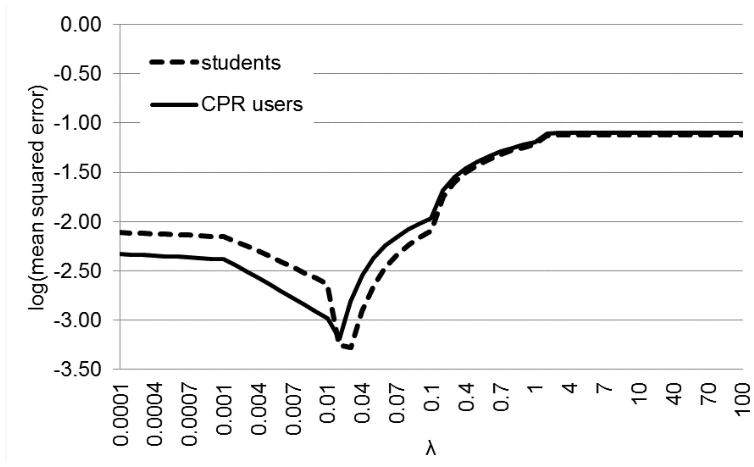
[7] If looking at the last-round effect in terms of the cooperative strategy (extract 1 unit) we see a slight reduction for students (8% to 7%) and an increase for real CPR users (12% to 14%), which speaks to the stylized finding that CPR users have the habit of *not finishing everything on the table*. See Figure A1 in the appendix

[8] Cárdenas, Mantilla, and Sethi, 2015 point out that QRE outperforms payoff sampling equilibrium under corner solutions. Given that both the social optimum and Nash equilibrium are corner solutions, this favors the use of QRE within our setting.

[9] Logit is the most common specification for a QRE. Assuming a symmetric equilibrium, errors ϵ_{ik} of individual i adopting strategy k are independent and identically distributed according to a type I extreme value distribution.

[10] λ indicates the degree of rationality: when $\lambda\to\infty$ (the error rate tends to zero) subjects are rational and when $\lambda=0$ subjects are acting randomly according to a uniform probability function.

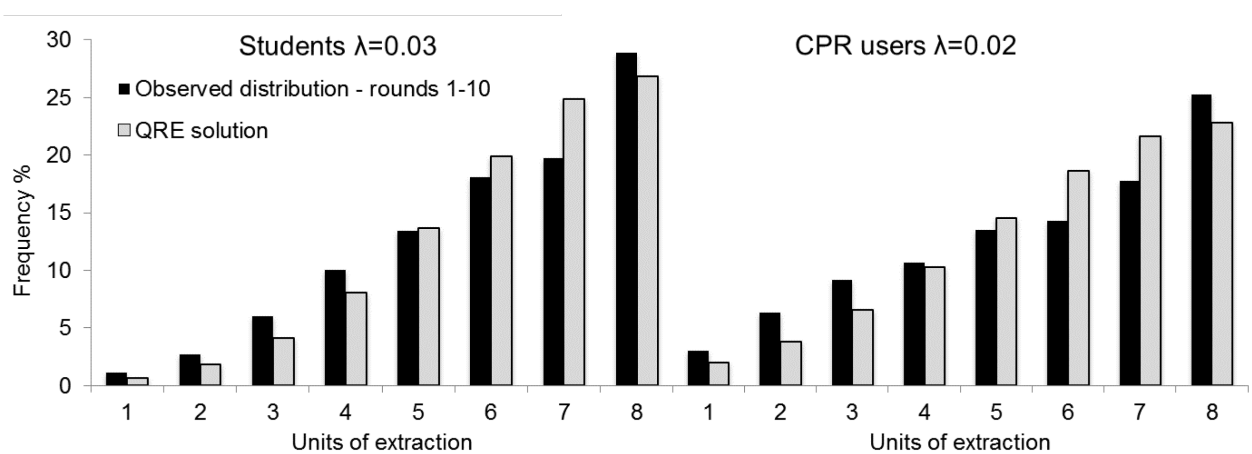
Figure 2.3.1: log(MSE) as a function of λ.



The value of λ minimizing MSE is very close across the samples: 0.03 for students and slightly lower for real CPR users at 0.02. Though this suggests a somewhat higher level of rationality among the student sample, the order of magnitude is the same. We take this as indicative evidence that using a constant λ across the population and across types is an adequate assumption (we normalize λ to 1).

Figure 2.3.2 compares the predicted and realized distributions. As Cárdenas, Mantilla, and Sethi, 2015 point out, a slightly better fit is achieved within the student sample ($MSE = 0.053\%$) than that of real CPR users ($MSE = 0.065\%$). In particular, the higher (respectively lower) incidence of payoff-maximizing (resp. socially efficient) behavior among students seem better matched by the QRE. However, and in spite of the overall constant trend over time (see figure 2.2.2) a lot of cross-sectional variation remains that cannot be explained using symmetric strategies. We now turn to a model of other-regarding preferences.

Figure 2.3.2: Observed distribution of choice outcomes and QRE distribution



2.4 A structural model of other-regarding preferences

We introduce a structural model to estimate preferences for altruism, self-regard, reciprocity and inequity aversion.

Type q is characterized by the utility function U^q where $\Theta = \{\rho, \mu, \beta\}$ is a vector of individual parameters for the individual utility function. We will consider the most popular types of individuals in the behavioral economics literature: i) self-regarding, ii) altruist, iii) reciprocator and iv) inequity averse. All these other-regarding preferences are defined over payoffs: they incorporate concerns over outcomes (as captured by the payoffs). Additionally, reciprocators exhibit preferences over behaviors.

As discussed in section 2.1, a general specification of preferences takes into account own payoff, others' payoff and others' behavior. Consequently, at each point in time each individual chooses a level of extraction in order to solve[11]

$$\max_{x_{it}} U^i(\pi_{it}, E_{t-1}[\overline{\pi}_{-it}], E_{t-1}[\overline{x}_{-it}]; \Theta) \tag{2.5}$$

where $E^i_{t-1}[\overline{\pi}_{-it}]$ denotes individual expectations about others' strategy, $\overline{\pi}_{-i} = \frac{\sum_{j \neq i} \pi_j}{n-1}$, given their information at hand (and similarly for $\overline{x}_{-it}$). Our previously discussed simpliying assumption about beliefs reads as

$$E^i_{t-1}[\overline{\pi}_{-it}] = \overline{\pi}_{-i,t-1} \text{ and } E^i_{t-1}[\overline{x}_{-it}] = \overline{x}_{-i,t-1} \tag{2.6}$$

Baseline: self-regarding preferences

Individuals that exhibit self-regarding preferences care only about their own monetary cost and benefits and are usually called in the literature as free-riders, self-regarding or defectors. A *self-regarding* individual i has a utility function given by $U^S = \pi_i$. Note that the (self-regarding) best reply is the maximum extraction level $x_i^S = 8$ and the Self-regarding Nash equilibrium is given by the maximum individual level of extraction or $x_i^{NE} = 8$ units in our CPR framework $\forall i$.[12]

Altruistic preferences

We adapt our CPR framework to the models proposed by Levine, 1998 and Casari and Plott, 2003. Individuals that exhibit these preferences are those who care about others' utility - i.e. altruists in Andreoni and Miller, 2002; Carpenter et al., 2009, unconditional cooperators in Fischbacher, Gächter, and Fehr, 2001 or pure cooperators in Rabin, 1993.

[11]For simplicity, we will be assuming linear individual utility functions, which translates expected payoffs into expected utilities. However, neutrality is an important matter measuring other-regarding preferences. The analysis becomes more complicated with other functional forms of the utility function.

[12]By construction the Nash equilibrium of the game is the stable strategic outcome from a game between self-regarding players.

An *altruist* has a utility given by

$$U^A = \pi_i + \rho\overline{\pi}_{-i} \quad \text{with } \rho \in (0,4]\forall i \tag{2.7}$$

where ρ is the parameter of altruism, the positive weight an altruist puts on others payoff.

Reciprocity

Our reciprocators are individuals that cooperate only if others cooperate and present similar behavior to conformism (Rabin, 1993; Bowles, 2004; Levine, 1998). When individuals do not have complete information about others behavior, they use the current social norms which stem from beliefs about others behavior. A **social norm** is a pattern of behavior such that individuals prefer to conform to it on the condition that they believe that most people in their reference network i) conform to it (i.e. empirical expectations) and ii) think they ought conform to the norm (i.e. normative expectations) (**Bichieri2014**; Bicchieri, 2005) . Given that decisions are private and individual in the CPR game, the game is able to capture empirical expectations the first time they play (i.e. the practice rounds). Empirical expectations are key for social norms to evolve and they are mostly based on observations of what individuals in the reference group have done in the past (Bicchieri, 2014). In addition, in repeated encounters, people have an opportunity to learn from each other's behavior, and to secure a pattern of reciprocity that minimizes the likelihood of misperception (Bicchieri and Muldoon, 2014). We then define x_i^* is an ethical prescription governing actions towards others, a social norm determined by culture, reference points or the context of individual behavior. In order to examine reciprocity, we use as social norm $x_i^* = \bar{x_0} = 4.89\forall i$ [13], the average number of extracted units in the last practice round among CPR users in the first visit since at that stage subjects had not formed their expectations on which types they were interacting with in their group.

A nonaltruistic Reciprocator individual i (exhibits neither good will nor spite unconditionally but conditions her behavior on the goodness or spitefulness of others) has a utility given by

$$U_i^R = \pi_i + \mu(x^{*i} - \overline{x}_{-i})\overline{\pi}_{-i} \;\forall\; i \tag{2.8}$$

where x^{*i} is a norm based on which i rates extractions from others, deriving more utility if others' extraction is below the norm and less otherwise. A positive value of μ would indicate a desire to uphold the social norm.

Polania-Reyes, 2015 estimate the structural parameters ρ and μ by means of a random coefficients model, which assumes idiosyncratic coefficients for each individual. Selfish behavior is identified as the opposite of selfless behavior as given by the value of ρ (ρ_i in her specification).

[13]We use $x_i^* = \bar{x_0} = 4.51$ for students

Fairness and inequity aversion

This model is based on Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000. We use the adaptation to a CPR model by Falk, Fehr, and Fischbacher, 2002. An *inequity averse* individual i has a utility given by

$$U_i^I = \pi_i + \alpha \max(\overline{\pi}_{-i} - \pi_i, 0) + \beta \max(\pi_i - \overline{\pi}_{-i}, 0) \; \forall \; i \tag{2.9}$$

The second term in equation 2.9 measures the utility loss from disadvantageous inequality, and the third term measures the loss from advantageous inequality. It is assumed that the utility gain from i's payoff is higher than her utility loss for advantageous inequality and her utility loss from disadvantageous inequality is larger than the utility loss if player i is better off than other players, $\beta \leq 0$. In addition, i is loss averse in social comparisons: i suffers more from inequality that is to his disadvantage (Loewenstein, Thompson, and Bazerman, 1989): $\alpha_i \geqslant \beta_i$.

Disadvantageous inequality can only be identified under interior solutions (Fehr and Schmidt, 1999; Falk, Fehr, and Fischbacher, 2002; Vélez, Stranlund, and Murphy, 2009). Because our CPR setting yields boundary solutions for both the Nash equilibrium and social optimum, our regression specification only incorporates advantageous inequality. The sign on β will identify preferences for inequity, if positive, and for equity otherwise.

Beliefs

The formulation of beliefs is as important as that of preferences. One of the basic insights behind QRE is that if agents make errors, they expect others to make the same mistakes. The formulation of beliefs raises an identification challenge. Expectations are closely linked to learning. Arifovic and Ledyard, 2012 provide a model that incorporates both other-regarding preferences (altruism, self-regarding and inequity aversion) and learning (through an Individual Evolutionary Model, IEM). An IEM is characterized by experimentation, replication and learning (each of these adding one free parameter to the model).

We assume agents only take into account other players' immediately preceding action. This simplification, which allows us to focus on the classification of behavioral types, is warranted by the fact that agents only learn previous round average extraction. A more detailed model of belief formation such as Arifovic and Ledyard, 2012 might add precision to the model, in return for more free parameters to be estimated, but it wouldn't help the identification procedure itself because of its reliance on symmetric cognitive profiles across players.

Summary: a mixture model without type identification

We suppose the population comprises 4 homogeneous (unobservable) types. On each round $t \in \{1, \ldots, T\}$, individual i makes her extraction decision x_{it} in order to maximize their utility, given the other 4 player's previous behavior in the group, $\overline{x}_{-it-1}$. We then define the structure of the error term as we introduce errors in decisions for each type and use a random utility specification in this choice environment. The expected utility takes the linear form for an individual type q, being self-regarding, inequity averse, reciprocator or altruist, $q \in \{S, I, R, A\}$. At time t, agent i chooses an action $j \in \{1, \ldots, J\}$ to derive utility

$$\tilde{U}^q(x_{ijt}; \theta_q, \overline{x}_{-it-1}) = U^q(x_{ijt}; \theta_q, \overline{x}_{-it-1}) + \varepsilon^q_{ijt} \quad \forall\, j \in \{1, \ldots, J\} \tag{2.10}$$

The choice probability, conditional on type q, is then determined by the logit function

$$\tilde{f}_q(x_{ijt}; \theta_q, \lambda_q, \overline{x}_{-it-1}) = \frac{\exp[\lambda_q U^q(x_{ijt}; \theta_q, \overline{x}_{-it-1})]}{\sum_{m=1}^{J} \exp(\lambda_q U^q(x_{imt}; \theta_q, \overline{x}_{-it-1}))} \tag{2.11}$$

This logit function is reminiscent of the QRE specification of section 2.3. As we argued back then, we will drop λ_q, $q \in \{S, I, R, A\}$ from the problem assuming a constant parameter applies throughout.

The individual contribution to the total likelihood function is the sum of the component densities $f_q(x_i; \theta_q, \overline{x}_{-i})$ weighted by the probabilities p_q that individual i belongs to type q such that $q \in Q = \{S, I, R, A\}$:

$$f(x_i; \Theta) = \sum_{q \in Q} p_q \prod_{t=1}^{T} \prod_{j=1}^{J} \left(f_q(x_i; \theta_q, \overline{x}_{-i})\right)^{d_{ijt}} \tag{2.12}$$

where d_{ijt} is a dummy for whether action j was indeed chosen at time t. This leads to the likelihood function

$$\ln L(\Psi; x) = \sum_{i=1}^{N} \ln f(x_i; \Psi) = \sum_{i=1}^{N} \ln \sum_{q \in Q} p_q f_q(x_i; \theta_q, \overline{x}_{-i}) \tag{2.13}$$

Assuming $U^q(x_{ijt}; \theta_q, \overline{x}_{-it-1}) = U(x_{ijt}; \theta_q, \overline{x}_{-it-1})$ where $\theta_q = \theta \sim F(.)$ allows us to estimate $\mathbf{p} = \{p_S, p_I, p_A\}$, $\Theta = \{\theta_q\} = \{\rho, \beta, \mu\}$ by direct maximization of

$$\ln L(\Psi; x) = \sum_{i=1}^{N} \ln f(x_i; \Psi) = \sum_{i=1}^{N} \ln \sum_{q \in Q} p_q \int_{-\infty}^{\infty} \left(f(x_i; \theta_q, \overline{x}_{-i})\right) \mathrm{d}F(\theta) \tag{2.14}$$

Among the structural preference models that take into account agent heterogeneity, this continuous mixture model is the most commonly used ((Cappelen et al., 2007; Cappelen, Sørensen, and Tungodden, 2010; Cappelen et al., 2011; Cappelen et al., 2013b), (Cappelen et al., 2013a), all of which assume a lognormal distribution for the parameters). In addition to the need for a predefined functional form for the continuous mixture, the finite mixture model does not allow the estimation of separate parameters for the different preference functions, i.e. $U^q(x_{ijt}; \theta_q, \overline{x}_{-it-1}) \neq U'^q(x_{ijt}; \theta_q, \overline{x}_{-it-1})$. Because this is precisely what we intend to do, we refine the formulation of p_q following a latent class model.

2.5 Type identification using a latent class model

In order to identify individual types, we use a latent class estimated using the Expectation Maximization (EM) algorithm (Dempster, Laird, and Rubin, 1977; Train, 2008). More specifically we follow an implementation of (Train, 2008) by Pacifico, 2012[14] using the specification in section 2.4.[15]

The simultaneous estimation of types and parameters relies on an iteration of two steps: one where likelihood conditional on types is maximized (the M-step) and one where idiosyncratic type distribution is updated.

The E-step

During the E-step, we take the conditional expectation of the complete-data log likelihood, $\ln L^c(\Psi)$ given the observed extraction profiles x, using the current fit for Ψ. Let $\Psi^{(0)}$ be the value specified initially for Ψ. Then on the first iteration of the EM algorithm, the E-step requires the computation of the conditional expectation of $\ln L^c(\Psi)$ given x, using $\Psi^{(0)}$ for Ψ:

$$G(\Psi, \Psi^{(0)}) = \mathbb{E}_{\Psi^{(0)}}[\ln L^c(\Psi)|X = x] \tag{2.15}$$

On the *(k + 1)*th iteration the E-step requires the calculation of $G(\Psi, \Psi^{(k)})$ where $\Psi^{(k)}$ is the value of Ψ after the kth EM iteration. Since $\ln L^c(\Psi)$ is linear in the unobservable υ_{iq}, it requires that $\mathbb{E}_{\Psi^{(k)}}(V_{iq}|X = x) = \tau_{iq}^{(k+1)}(x; \Psi^{(k)})$ [16], where V_{iq} is the random variable corresponding to υ_{iq} and[17]

$$\tau_{iq}^{(k+1)}(x; \Psi^{(k)}) = \frac{p_q^{(k)} f_q(x_i; \theta_q^{(k)}, \overline{x}_{-i})}{\sum_{q \in Q} p_q^{(k)} f_q(x_i; \theta_q^{(k)}, \overline{x}_{-i})} \tag{2.16}$$

are the *a posteriori* probabilities that the ith member of the sample with observed value x_i belongs to the qth component of the mixture, computed according to Bayes law given the actual fit to the data, $\Psi^{(k)}$. Then

$$G(\Psi, \Psi^{(k)}) = \sum_{i=1}^{N} \sum_{q \in Q} \tau_{iq}^{(k+1)}(x_i; \Psi^{(k)}, \overline{x}_{-i})[\ln p_q^{(k)} + \ln f_q(x_i; \theta_q^{(k)}, \overline{x}_{-i})] \tag{2.17}$$

[14] We use the Stata module developed by Pacifico, 2012 called lclogit

[15] The model specification is time-invariant, which implies that $\upsilon_{qt} = \upsilon_q$. Kasahara and Shimotsu, 2009 study type identification in finite mixture models with panel data.

[16] $\mathbb{E}_{\Psi^{(k)}}(V_{iq}|X = x) = Pr_{\Psi^{(k)}}[V_{iq} = 1|X = x]$ is the current conditional expectation V_{iq} of given the observed data $X = x$

[17] $f(x_i; \Psi^{(k)}, \overline{x}_{-i}) = \sum_{q \in Q} p_q^{(k)} f_q(x_i; \theta_q^{(k)}, \overline{x}_{-i})$

The M-step

The M-step on the *(k + 1)*th iteration, the complete-data log likelihood function 2.17 is maximized with respect to $\Psi^{(k)}$ to provide the updated estimate $\Psi^{(k+1)}$.[18]

As the E-step involves replacing each v_{iq} with its current expectation $\tau_{iq}^{(k+1)}(x; \Psi^{(k)})$ in the complete-data log likelihood, the updated estimate of p_q is giving by replacing each v_{iq} in (23):

$$\widehat{p_q}^{(k+1)} = \sum_{i=1}^{N} \frac{\tau_{iq}^{(k+1)}(x_i; \Psi^{(k)}, \overline{x}_{-i})}{N} \tag{2.18}$$

Dempster, Laird, and Rubin, 1977 show that the sequence of likelihood values $\{L(\Psi^{(k+1)})\}$ is bounded and non-decreasing from one iteration to the next, so the EM algorithm converges monotonically to its maximum. The E- and M-steps are thus alternated repeatedly until the difference $L(\Psi^{(k+1)}) - L(\Psi^{(k)})$ changes by a -previously fixed- arbitrarily small amount.

Note that these posterior probabilities of individual group membership are not only used in the M-step, but they also provide a tool for assigning each individual in the sample to one of the Q types. Thus, finite mixture models may serve as statistically well grounded tools for endogenous individual classification (Bruhin, Fehr-Duda, and Epper, 2010).

Testing for the number of types

An important aspect of the contribution by (Arifovic and Ledyard, 2012) is that reciprocity arises not as a type but as an equilibrium behavior. This raises the empirical question of whether reciprocity can be thought of as an attribute. We provide some empirical information to this question by testing for the optimal number of types using a latent class model to fit the data.

Table 2.1 summarizes the performance of a different number of factors for the sample of real CPR users along the dimensions of information (as measured by the Consistent Akaike Information Criterion and Bayesian Information Criterion) and of likelihood (as measured by the likelihood ratio).

Table 2.1 also provides evidence that the optimal model to describe the data is either one with 4 classes, the information criteria such as the CAIC or the BIC being less prone to overparametrization than the likelihood criterion. Table 2.2 presents similar results for the student sample.

[18] For the FMM the updated estimates $p_q^{(k+1)}$ are calculated independently of the update estimate $\boldsymbol{\xi}^{(k+1)}$ of the parameter vector containing the unknown parameters in the component densities. See (Cappelen et al., 2007; Cappelen, Sørensen, and Tungodden, 2010; Cappelen et al., 2011; Cappelen et al., 2013b; Cappelen et al., 2013a)

Table 2.1: Comparison of model performance by number of types - CPR users sample

No. classes	LL	No. parameters	BIC	CAIC
2	-6992.937	21	14144.6	14123.6
3	-6887.851	38	14062.91	14024.91
4	-6821.428	55	**14058.56**	**14003.56**
5	-6783.39	72	14110.97	14038.97
6	**-6761.148**	89	14194.98	14105.98

The picture arising from the student sample (table 2.2) is not exactly the same as from that of real CPR users, as it seems to suggest the use of a fifth class. In the absence of theoretical support for the additional class, our observation is that the results found across the two populations are in broad agreement.

The results so far support the use of four types, which according to our theoretic model are the self-regarding, altruistic, inequity averse and reciprocators.

Table 2.2: Comparison of model performance by number of types - Student sample

No. classes	LL	No. parameters	BIC	CAIC
2	-4045.653	9	8149.25	8140.25
3	-3999.159	14	8088.451	8074.451
4	-3981.109	19	8084.542	8065.542
5	-3956.442	24	**8067.399**	**8043.399**
6	**-3948.002**	29	8082.708	8053.708

Latent class model results

Utility parameters: coefficients and labels

Table 2.3 provides the results for the class share determinants model estimated with the real CPR user sample. In order to understand the type classification above, we now examine the drivers for the probability of belonging to each type. Across specifications the composition is similar. Inequity aversion occupies a large share within the real CPR user sample: most real CPR users are affected negatively by advantageous inequality in their payoffs. Pure self-regarding and pure altruists make up a smaller share of the sample, very close to the random coefficients model outcome in Polania-Reyes, 2015 using a (10% altruists, 7% self-regarding).

Table 2.3: Type classification and structural parameters - CPR users and students

	CPR users sample				Students
Specification	I	II	III	IV	V
Type composition					
p_S	0.15	0.14	0.11	0.12	0.02
p_R	0.08	0.09	0.11	0.11	0.13
p_I	0.72	0.70	0.73	0.71	0.74
p_A	0.06	0.07	0.05	0.06	0.11
Theoretical parameters					
ρ	1.09	1.02	1.06	1.08	1.31
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
β	-1.27	-1.24	-1.10	-1.13	-1.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
μ	-0.10	-0.09	-0.12	-0.12	0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
conditional on					
Socioeconomic characteristics	No	Yes	Yes	Yes	-
CPR use	No	No	Yes	Yes	-
Social capital	No	No	No	Yes	-

Standard errors in parenthesis

As discussed before, the negative sign on the weight to own payoff is at first sight unsettling, but highlights the nature of the social dilemma. In making a distinction between altruism and concern for efficiency, the presence of a negative coefficient argues for altruism in the present case.

Only a small percentage in our sample are reciprocators (to the point of Arifovic and Ledyard, 2012). Here we are far from the results in Polania-Reyes, 2015 where a high incidence of reciprocating behavior is found. We note that her random coefficient model cannot accommodate inequity aversion and has a high share of unidentified types (32%). This limits the interpretability and comparability of results across the two studies. The negative sign on the concern for the norm is counterintuitive and suggests a specification issue in our function, possibly in how the social norm itself is defined.

In order to compare estimates across populations, we constrain the coefficients on the student sample so that the weight on own payoff matches the one from the real CPR user sample.[19] The results are recorded in table 2.3.

Again we observe a large number of inequity averse individuals (with a similar magnitude for the utility parameter), similar to the results from the real CPR user sample. In stark contrast, when trying to match altruistic behavior we end up with a negative coefficient.

[19]See alternative specifications in appendix 2.6

Interpreted directly this coefficient points to spiteful behavior, whereby agents are affected negatively by both their outcomes and those of others. Polania-Reyes, 2015 does not provide a point of comparison on the student sample.

Our latent class estimate allows to make choice prediction. In order to understand the relative performance of each model, we document the choice prediction outcome below. So far we haven't taken advantage of the data from rounds 11 to 20. We do so now by comparing the model performance in-sample (rounds 1 to 10) and out-of-sample (rounds 11 to 20).

A naive model (e.g. our static QRE) can only attain a 1/8 choice probability, which is improved within all classes except that of reciprocators, in line with the concern expressed previously about this category. The out-of-sample performance is comparable (sometimes slightly higher) than in-sample, something we take as an important sign of internal validity. In terms of relative performance, the altruistic-spiteful category performs better than the rest, and better still than the self-regarding category. This is a surprising finding, given that the Nash strategy is expected to be more stable (hence a priori more predictable) than others.

Table 2.4: Class-conditional probability of choice

Class	Villagers		Students	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Self-regarding	0.173	0.166	0.205	0.189
Altruistic / Spiteful	0.314	0.437	0.336	0.341
Inequity averse	0.164	0.210	0.173	0.217
Reciprocator	0.136	0.064	-	-

Class share determinants

A key feature of heterogeneity is the role of individual background. For example, the use of CPR in real life by the participants. Figure 2.5.1 shows the fraction of players that extract 8 units according to their dependence to the CPR. Those users whose income depends 100% on the CPR extract significantly less whereas those users whose income depends 0% on the CPR extract significantly more. Those who in real life depend more on the common pool resource have a lower probability of being allocated to the self-regarding type.

Figure 2.5.1: Heterogeneity of real level extraction of the CPR in the game all CPR users vs. students ($N = 1095$). The solid line shows the % time that the Self-regarding NE was chosen in the game by the Students sample. The round-dot line shows the case with individuals who use 0% of the real CPR. The square-dot line shows the average level of extraction in the game by individuals who use 50% of the real CPR. The long-dashed line the average level of extraction in the game by individuals who use 100% of the real CPR. The difference in means in the last round is significant at 10%.

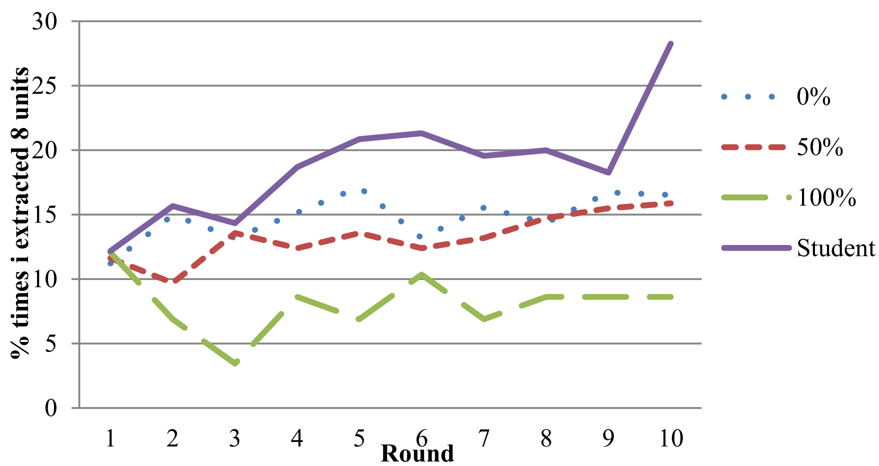


Table 2.5: Drivers of class share - real CPR user sample

Specification	II			III			IV		
	S	R	I	S	R	I	S	R	I
Age	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Education level	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.3	0.0	-0.1
Kitch_elect	-1.4	-1.0	-1.2	-1.5	-0.4	-1.1	-0.5	-0.7	-1.
Kitch_gas	-0.5	0.6	-0.4	-1.5	0.2	-1.4	-1.2	0.8	-1.2
Land owner	0.3	-0.2	0.4	0.4	0.4	0.8	0.3	0.3	0.6
HH size	-0.2	-0.1	-0.1	-0.3	-0.2	-0.2	-0.3	-0.2	-0.2
Sex	-0.1	-0.3	-0.1	-0.4	-0.3	-0.3	0.0	-0.1	0.1
Voluntary work				-0.2	-0.4	-0.8	-0.3	-0.3	-0.7
Perceived good Governance				-0.3	0.1	0.1	-0.1	0.4	0.3
Perceived common interest				0.1	0.2	-0.1	-0.2	0.0	-0.3
CPR_still_perceived							-0.5	-1.3	-0.6
HH_income_CPR							-0.7	1.1	0.6

S: Self-regarding, R: Reciprocator, I: Inequity averse. Altruists are the benchmark group

Those users whose income depends 100% on the CPR are more likely altruistic or inequity averse than those whose income doesn't. The belief that the community has no need of an external authority to rule them increases the likelihood of altruistic or inequity averse classification, and decreases that of the self-regarding one. The perception that the resource will remain still greatly decreases the likelihood of being altruistic as opposed to self-regarding. Voluntary participation, instead, shows a counterintuitive role, leading to a lower probability of being inequity averse and instead a higher probability of being self-regarding.

2.6 Conclusion

This is a study on type classification for other-regarding preferences from a CPR game. We bring a novel method to identify types in a unique sample including real CPR users and students. We examine the most popular types of other-regarding preferences in the theory literature, testing for the optimal number of types. Our structural estimation relies on four types, which the data supports. The most salient feature is the prevalence of aversion to inequity across both samples. There is evidence both of pure altruistic behavior in the real CPR users' sample and of spiteful behavior among students. The lack of empirical evidence for reciprocal types sheds doubt on our specification, but also gives an indirect signal that reciprocity arises not as a type but as an equilibrium behavior across types.

Using an RCM classification, (Polania-Reyes, 2015) finds that non-monetary incentives are more effective in groups where other-regarding preferences are prevalent and only the subsidy is effective in promoting behavior among self-regarding individuals. While we leave aside the treatment of incentives, we note that types are likely to be state dependent. Our finding that in-sample and out-of-sample model outcomes are comparable provide internal validity to our findings. This is particularly important in the latent class literature where, as previously discussed, labels are commonly found to be driven by data rather than theory.

We acknowledge the importance of beliefs in the decision making progress. Facing the possibility of heterogeneous preferences as well as that of heterogeneous learning, we shut down the latter to focus on the former. We assume an overly simplistic system of beliefs, namely that agents only take into account what others did in the previous round. While an IEM type model would take into account the likely higher complexity of the thought process (at the cost of parsimony), an identification challenge remains in terms of the two types of heterogeneity (cognitive and behavioral). The development of heterogeneous QRE under cognitive hierarchies proposed by Rogers, Palfrey, and Camerer, 2009 might be helpful in that sense. Our conjecture is that cognition and other-regarding preferences are correlated, suggesting the importance of identifying such correlations.

Testing and identification remain a challenge, both for a model of other-regarding preferences or for a pure model of bounded rationality such as QRE (McCubbins, Turner, and Weller, 2013). On one hand, classical competive behavior might obtain in an economy subject to other-regarding preferences (Dufwenberg et al., 2011). On the other hand, there is evidence that other-regarding preferences are subject to framing effects (Dariel, 2013; Ackermann, Fleiß, and Murphy, 2014) or the institutional setting (Cassar, d'Adda, and Grosjean, 2013).

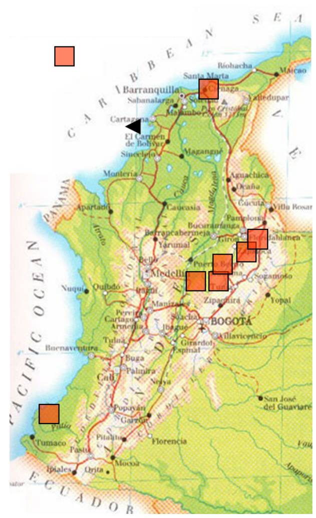
Group composition is indeed a key feature. While we restrict ourselves to variables at the individual level, Polania-Reyes, 2015 performs a regression analysis with a probit model where the probability of being type q depends on socioeconomic characteristics at the individual and village level. She finds community level drivers are important, and in particular that types are somewhat correlated. If types are robust over time (as the evidence discussed here suggests) yet at the same time context- or group-dependent, an evolutionary approach might be fitting not only for the learning but also the behavioral aspect of choice in CPR settings as well as similar collective action problems.

Appendix

Tables

Table 2..1: Labs in the field

Villages	*CPR*
Providencia	Coral reefs
	Coastal fisheries
	Crab gatherers
Gaira	Coastal fisheries
Sanquianga	Clams
	Fisheries
	Shrimp
	Mangroves
Barichara	Andean Forests
Chaina	Firewood
Tabio	Andean Forests
	Water
La Vega	Water
Neusa	Dam reservoir
	Trout fishing



Note: the red squares are the villages.

Table 2..2: Table points of the CPR game.

	Others	**My Level of Extraction from the Resource**								Others
Total Level of the extraction by others	Total	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	Average
	4	758	790	818	840	858	870	878	880	1
	5	738	770	798	820	838	850	858	860	1
	6	718	750	778	800	818	830	838	840	2
	7	698	730	758	780	798	810	818	820	2
	8	678	710	738	760	778	790	798	800	2
	9	658	690	718	740	758	770	778	780	2
	10	638	670	698	720	738	750	758	760	3
	11	618	650	678	700	718	730	738	740	3
	12	598	630	658	680	698	710	718	720	3
	13	578	610	638	660	678	690	698	700	3
	14	558	590	618	640	658	670	678	680	4
	15	538	570	598	620	638	650	658	660	4
	16	518	550	578	600	618	630	638	640	4
	17	498	530	558	580	598	610	618	620	4
	18	478	510	538	560	578	590	598	600	5
	19	458	490	518	540	558	570	578	580	5
	20	438	470	498	520	538	550	558	560	5
	21	418	450	478	500	518	530	538	540	5
	22	398	430	458	480	498	510	518	520	6
	23	378	410	438	460	478	490	498	500	6
	24	358	390	418	440	458	470	478	480	6
	25	338	370	398	420	438	450	458	460	6
	26	318	350	378	400	418	430	438	440	7
	27	298	330	358	380	398	410	418	420	7
	28	278	310	338	360	378	390	398	400	7
	29	258	290	318	340	358	370	378	380	7
	30	238	270	298	320	338	350	358	360	8
	31	218	250	278	300	318	330	338	340	8
	32	198	230	258	280	298	310	318	320	8

Note: The Self-regarding Nash Equilibrium produces an individual payoff of 320MU whereas the social optimum leads to an individual payoff of 758 MU.

Table 2..3: Real Users' Socio-economic Characteristics

Variable		**Mean**	**Median**	**Min.**	**Max**	**SD**	**%N**
HH Size		5.59	5	1	51	3.1	87
Age average		34.0	32	7	85	13.9	88
Woman(==1)		46.9	0			49.9	88
Years of education (average)		6.0	5	0	18	3.7	81
Landowners %		75.0	1			43.3	87
Membership %		46.3	0			0.5	95
Meetings Attendance %		11.3	1	0	2080	89.9	77
Perception cooperation %		46.5	50	0	75	28.0	82
Perception interest in CPR	%	62.5	30			37.6	76
Community should control	%	59.7	50	-1	1	42.6	85
Fraction of players with	100%	22.0					
Extraction of the CPR as	50%	65.2					88
main economic activity	0%	12.8					

Figures

Figure 2..1: Timeline of the CPR game

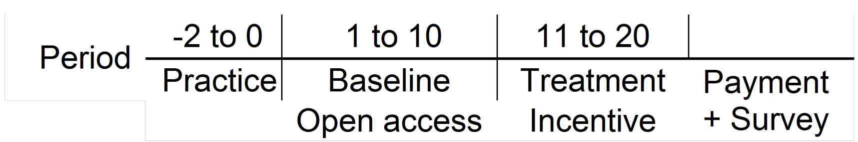


Table 2..4: Class share determinants (student sample) without the restrictions coming from the real CPR users' model

Variable	Self-regarding	Spiteful	Inequity averse	Reciprocators	Std. error
π_i	-0.017	-0.049	0.026	0.043	0.002
$\overline{\pi}_{-i}$	0^a	-0.064	0^a	0^a	0.000
$\max(\pi_i - \overline{\pi}_{-i}, 0)$	0^a	0^a	-0.029	0^a	0.001
$\overline{\pi}_{-i}(x^{i*} - \overline{x}_{-i})$	0^a	0^a	0^a	0.001	0.000
Class Share	0.240	0.107	0.740	0.130	-

[a] Constrained to 0 in estimation

Table 2..5: Class share determinants (student sample) without any restrictions

Variable	Class 1	Class 2	Class 3	Class 4	Std. error
π_i	-0.017	0.058	-0.042	0.010	0.002
$\overline{\pi}_{-i}$	-0.039	0.014	-0.123	-0.053	0.002
$\max(\pi_i - \overline{\pi}_{-i}, 0)$	-0.044	-0.054	-0.056	-0.048	0.000
$\overline{\pi}_{-i}(x^{i*} - \overline{x}_{-i})$	-0.006	-0.018	-0.014	-0.015	0.000
Class Share	0.216	0.137	0.193	0.453	-

[a] Constrained to 0 in estimation

Figure 2..2: Baseline: behavior over rounds for Pure Self-regarding and Pure cooperator

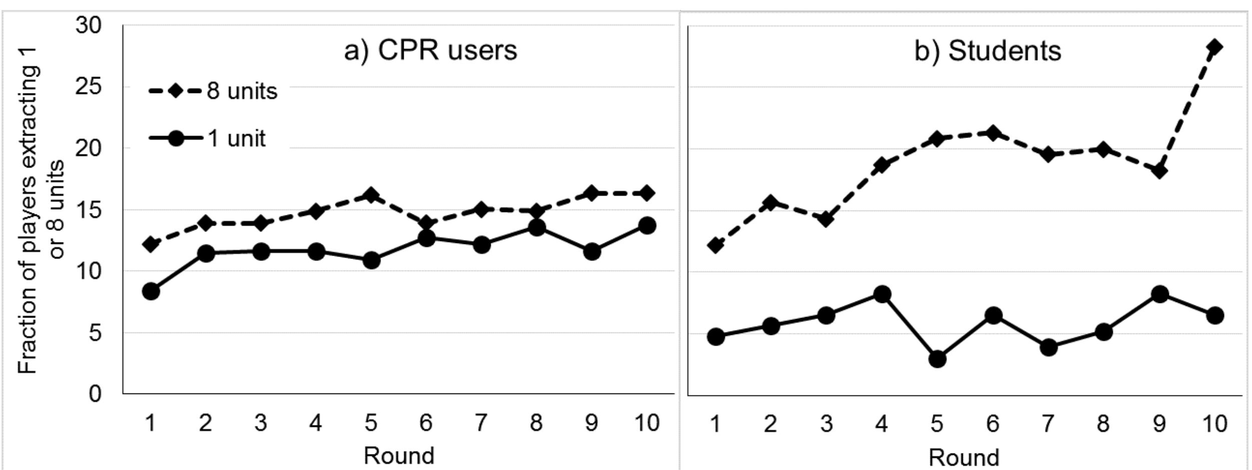


Table 2..6: Class share determinants (real CPR user sample) without any restrictions

Variable	Class 1	Class 2	Class 3	Class 4	Std. error
π_i	-0.005	-0.018	-0.203	0.030	0.001
$\overline{\pi}_{-i}$	-0.045	-0.028	-0.196	-0.104	0.001
$\max(\pi_i - \overline{\pi}_{-i}, 0)$	-0.037	-0.043	-0.071	-0.073	0.000
$\overline{\pi}_{-i}(x^{i*} - \overline{x}_{-i})$	-0.011	-0.012	-0.026	-0.019	0.000
Class Share	0.631	0.243	0.027	0.098	-

[a] Constrained to 0 in estimation

Results of the latent class model under alternative specifications

Experimental protocol

Labs in the field Data

The experiments were conducted in 8 Colombian villages (see Figure 1) during 2001 and 2002 and a university in Bogotá. A total of 1095 participants attended the sessions, 230 undergraduate students and 865 real users of a CPR. Every village may depend on a different CPR (see Table 2..1).

All data were collected using standard procedures in experimental economics in the laboratory: no deception, no field referents, fully salient choices. We collected information on individual characteristics of the real CPR users only.

Experimental stages

The following stages were conducted for each of the sessions. This is cited by Cárdenas, 2011.

Pre-game Stage (Instructions and Practice Rounds)
Each session of an experiment began with the welcoming and reading of the instructions to the group of five players, as well as the handing out of the following forms (available from author): the GAME CARDS, where participants wrote their choice for every round, that is, their extraction level; the DECISIONS RECORDS SHEET, where participants kept records of their choices and earnings; and the PAYOFF TABLE (see Table 2..2). Once all questions from participants were clarified, the experimenter continued by conducting one or two practice rounds as examples (see Figure 2..1). After resolving all outstanding questions, stage 1 began.

Stage 1 (Rounds 1 to 10)
In Stage 1 of the experiment, each of the players had to decide privately their individual level of extraction from the commons. The decision was written down on one yellow slip (game card); the same information was also recorded on the blue records sheet. The monitor collected the five slips, added the total extraction for the group, which he wrote on the monitor's record sheet, and then announced publicly the total. Each player had to write down the group's total; by subtracting his or her individual extraction, the player was able to calculate his or her payoff for that round using the payoffs table. The player then wrote his or her total gains for the round and the experiment

proceeded to the next round with the filling of a new slip. Under such rounds, it was common information that round 10 was the final round. Once they had finished calculating their earnings for round 10, players were told that the rules of the exercise were going to change for Stage 2 of the game. Additionally, they were never told in advance what the rules for Stage 2 were.

Stage 2 (New Rules, Rounds 11 to 20)

The second stage began with the announcement that they would be playing another 10 rounds under a new set of rules. For this stage, the previous record sheets were collected and new ones were distributed among the five players. For the case of face-to-face communication, we began Stage 2 by indicating to the participants that in every round, and prior to their making their decisions, they would be allowed to have a 3 to 5 min discussion on anything they wanted concerning the developments of the game, though no arrangements would be allowed for redistributing earnings once the experiment had ended. However, they were told that decisions would remain private and confidential. For the groups under the regulation treatments, Stage 2 began with an explanation from the experimenter in the following terms.

The experimenter reminded the group that they had probably noticed that the group could earn the maximum of points if every player chose a level of extraction equal to one unit (this information was not given to the communication groups however). They were also told that for achieving such a goal, the monitor would choose one player randomly for every round, and would verify his or her compliance with the stated rule. The probability of such inspection was of 0.2, and was conducted by drawing a ball with a number from 5 balls in a bag. If a player was inspected and had chosen a higher level of extraction, his or her earnings were reduced by $50 ($175 for the high penalty treatment) times the units of extraction above 1. In the case where there was no fine, the monitor announced publicly the extraction level of the randomly chosen player, and proceeded to the next round. We also had control groups under a baseline treatment, with no change in the rules for Stage 2[20].

The text of the rule is the following: "You may have noticed that if each player in the group chooses a level of extraction of 1 unit the group makes the maximum possible of points. With this rule we will try that the group earns the maximum possible. We will try with this rule that each player in your group chooses a LEVEL OF EXTRACTION of 1 unit."

The Exit Stage (Calculating Earnings, Filling Out the Survey)

Following all of the rounds from Stage 2, the monitors calculated the total earnings for each player by adding the column of round earnings and subtracting the cases where a fine was imposed. While the monitors made the calculations, the players responded to the exit survey, anonymously and in private. Upon returning the filled survey, payments were made in cash to each player and in private.

Experimental instructions from Cárdenas, 2005:268-265

These instructions were originally written in Spanish and translated from the final version used in the field work. The instructions were read to the participants from the script below by the

[20]The reason for announcing this was to make sure that the players had a benchmark with which to compare when facing a penalty if chosen for inspection; also to ensure that the external policy was common knowledge. For many sessions, it was very clear that, by round 10 of the first stage, this was the social optimum solution for many of the players. On no single occasion was such a solution questioned, although participants were not allowed to formulate questions prior to stage 2.

same person during all sessions. The participants could interrupt and ask questions at any time. Whenever the following type of text and font e.g. [...MONITOR: distribute PAYOFFS TABLE to participants...] is found below, it refers to specific instructions to the monitor at that specific point; when in italics, these are notes added to clarify issues to the reader. Neither of these were read to participants. Where the word poster appears, it refers to a set of posters we printed in very large format with the payoffs table, forms, and the three examples described in the instructions. These posters were hung on a wall near the participants desks where the eight people could see them easily.

COMMUNITY RESOURCES GAME (Instructions)

Greetings...

We want to thank everyone here for attending the call, and specially thank the field practitioner XX (name of the contact person in that community), and XX (local organization that helped in the logistics) who made this possible. We will spend about two hours between explaining the exercise, playing it and finishing with a short survey at the exit. So, let us get started. The following exercise is a different and entertaining way of participating actively in a project about the economic decisions of individuals. Besides participating in the exercise, and being able to earn some prizes and some cash, you will participate in a community workshop in two days to discuss the exercise and other matters about natural resources. During the day of the workshop we will give you what you earn during the game. The funds to cover these expenditures have been donated by various international organizations and the University.

Introduction

This exercise attempts to recreate a situation where a group of families must make decisions about how to use the resources of, for instance, a forest, a water source, a mangrove, a fishery, or any other case where communities use a natural resource. In the case of this community XX (name of the specific village), an example would be the use of firewood or logging in the XX (name of an actual local commons area in that village) zone. You have been selected to participate in a group of five people among those that signed up for playing. The game in which you will participate now is different from the ones others have already played in this community, thus, the comments that you may have heard from others do not apply necessarily to this game. You will play for several rounds equivalent, for instance, to years or harvest seasons. At the end of the game you will be able to earn some prizes in kind and cash. The cash prizes will depend on the quantity of points that you accumulate after several rounds.

The PAYOFFS TABLE

To be able to play you will receive a PAYOFFS TABLE equal to the one shown in the poster. [... MONITOR: show PAYOFFS TABLE in poster and distribute PAYOFFS TABLE to participants...] This table contains all the information that you need to make your decision in each round of the game. The numbers that are inside the table correspond to points (or pesos) that you would earn in each round. The only thing that each of you has to decide in each round is the LEVEL OF EXTRACTION that you want to allocate extracting resources (in the columns from 1 to 8).

To play in each round you must write your decision number between 1 and 8 in a yellow GAME CARD like the one I am about to show you. [...MONITOR: show yellow GAME CARDS and show in the poster...] It is very important that we keep in mind that the decisions are absolutely individual, that is, that the numbers we write in the game card are private and that we do not have to show them to the rest of members of the group if we do not want to. The monitor will collect the 5 cards from all participants, and will add the total units of extraction that the group decided to allocate. When the monitor announces the group total, each of you will be able to calculate the points that you earned in the round. Let us explain this with an example. In this game we assume that each player extract as maximum of 8 units of a resource like firewood or logs. In reality this number could be larger or smaller but for purposes of our game we will assume 8 as maximum. In the PAYOFFS TABLE this corresponds to the columns from 1 to 8. Each of you must decide from 1 to 8 in each round. But to be able to know how many points you earned, you need to know the decisions that the rest in the group made. That is why the monitor will announce the total for the group in each round. For instance, if you decide to extract 2 units and the rest of the group together, add to 20 units, you would gain XX points. Let us look at two other examples in the poster.[...MONITOR: show poster with the THREE EXAMPLES...] Let us look how the game works in each round.

The DECISIONS FORM

To play each participant will receive one green DECISIONS FORM like the one shown in the poster in the wall. We will explain how to use this sheet. [...MONITOR: show the DECISIONS FORM in the poster and distribute the DECISIONS FORMS...] With the same examples, let us see how to use this DECISIONS FORM. Suppose that you decided to play 5 units in this round. In the yellow GAME CARD you should write 5. Also you must write this number in the first column A of the decisions form. The monitor will collect the 5 yellow cards and will add the total of the group. Suppose that the total added 26 units. Thus, we write 26 in the column B of the decisions form. [...MONITOR: In the poster, write the same example numbers in the respective cells...] To calculate the third column (C), we subtract from the group total, MY DECISION and then we obtain THEIR LEVEL OF EXTRACTION which we write in column C. In our example, 265 = 21. If we look at the PAYOFFS TABLE, when MY EXTRACTION are 5 and THEIR EXTRACTION are 21, I earn XX points. I write then this number in the column D of the DECISIONS FORM. It is very important to clarify that nobody, except for the monitor, will be able to know the number that each of you decides in each round. The only thing announced in public is the group total, without knowing how each participant in your group played. Let us repeat the steps with a new example. [...MONITOR: Repeat with the other two examples, writing the numbers in the posters hanging in the wall...] It is important to repeat that your game decisions and earnings information are private. Nobody in your group or outside of it will be able to know how many points you earned or your decisions during rounds. We hope these examples help you understand how the game works, and how to make your decisions to allocate your UNITS OF EXTRACTION in each round of the game. If at this moment you have any question about how to earn points in the game, please raise your hand and let us know. [...MONITOR: pause to resolve questions...] It is very important that while we explain the rules of the game you do not engage in conversations with other people in your group. If there are no further questions about the game, then we will assign the numbers for the players and the rest of forms needed to play.

Preparing for playing

Now write down your player number in the green DECISIONS FORM. Write also the place XX and the current date and time XX. In the following poster we summarize for you the steps to follow to play in each round. Please raise your hand if you have a question. [MONITOR: Read the steps to them from the poster] Before we start, and once all players have understood the game completely, the monitor will announce one additional rule for this group. To start the first round of the game we will organize the seats and desks in a circle where each of you face outwards. The monitor will collect your yellow game cards in each round. Finally, to get ready to play the game, please let us know if you have difficulties reading or writing numbers. If so, one of the monitors will sit next to you and assist you with these. Also, please keep in mind that from now on there should be no conversation nor should statements be made by you during the game, unless you are allowed to. We will first have a few rounds of practice that will NOT count toward your real earnings, they are just for practicing the game.

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