Complex Securities and Underwriter Reputation: Do Reputable Underwriters Produce Better Securities?

John Griffin
University of Texas, Austin

Richard Lowery
University of Texas, Austin

Alessio Saretto
University of Texas, Dallas

Conventional wisdom suggests that high-reputation banks will generally produce good securities to maintain their long-run reputation. We show with a simple model that, when securities are complex a high-reputation bank may produce assets that underperform during market downturns. We examine this possibility using a unique sample of $10.1 trillion of CLO, MBS, ABS, and CDOs. Contrary to the conventional view, securities issued by more reputable banks did not outperform but, rather, had higher proportions of capital in default. (*JEL* G240, G120, G390)

Although there is no shortage of opinions and news commentary, little academic research examines the role of the issuers in creating trillions of dollars of structured products. Much conventional wisdom, theory, and empirical evidence suggest that reputable banks work in the best interest of their clients because it is in the best interest of banks to do so. This paper examines this common perception of the incentives provided to a bank by its reputation as it

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relates to the recent performance of CLO, MBS, ABS, and CDOs issued over the previous decade.

The conventional view is concisely articulated by legendary Goldman Sachs partner, Gus Levy: "We're greedy, but long-term greedy, not short-term greedy" (Endlich 1999). The basic intuition is that it takes time to build a reputation, so a bank with a high reputation would never want to be so short-sighted as to maximize current profits at the expense of jeopardizing streams of future revenues. This intuition is also supported in many standard models of reputation and product quality, including Booth and Smith (1986) and Chemmanur and Fulghieri (1994) in finance and Liu (2011) and Mailath and Samuelson (2006) in game theory. We show that this intuition can break down with complex securities, and we confirm our theoretical prediction by analyzing a very large sample of structured finance products.

Our model employs a standard setting in which high reputation corresponds to a positive probability of an agent being committed to actions that are in the best interest of the investor. We consider a two-period reputation model and focus on two key elements of securitization: first, underwriters can exert some control over the security's pay-off in good and bad economic states by choosing the collateral quality and the degree of correlation between assets. Second, the securities are sufficiently complex that investors are not able to perform a counterfactual analysis to learn how securities would perform in an economic state different than the one they observe. The investor only learns the payoff in the bad state when the bad state actually occurs. On the contrary, if the securities are simple, as is the case in most standard reputation models, investors learn their quality in both the good and bad states.

Together, the two above characteristics can reverse the conventional wisdom of the effect of reputation on performance. Instead of providing discipline and leading to the production of good securities, high reputation may create incentives that lead a strategic underwriter to create bad securities. The mechanism is simple: a strategic underwriter who values his reputation can either imitate a commitment type or produce a security that pays off well in the good state at the expense of payoffs in the bad state—a "time-bomb" security. In structured finance, this can be accomplished by collateralizing low-quality, highly correlated assets, while representing them as of high quality and of low correlation. With complex securities, the inability of investors to perform counterfactual analysis allows the underwriter to produce low-quality securities and yet maintain his reputation in the good state at a much lower cost than if he were to fully imitate the commitment type. Our results show that strategic, high-reputation underwriters will mix between producing high and low-quality securities.

When the perceived commitment probability corresponds to the true proportion of committed players, there will be two countervailing effects that determine the average quality of the security produced by high-reputation underwriters. Commitment types will produce good securities, but strategic players with high reputation produce some very bad securities. In equilibrium, unless the fraction of commitment types is particularly high, the quality of securities created by high-reputation underwriters is on average worse than that created by underwriters with low reputation (i.e., those that have zero commitment probability). In summary, whether we consider the incentive of high-reputation strategic underwriters or whether we compare underwriters of high versus low reputation, we obtain a negative relation between reputation and the quality of the securities produced.

We evaluate the core empirical predictions of the model, as well as other features of the market, by analyzing a novel Bloomberg database consisting of over 10.1 trillion USD in underlying collateral covering collateralized loan obligations (CLO), nonagency mortgage-backed securities (MBS), asset-backed securities (ABS), and collateralized debt obligations (CDO). The sample consists of 132,401 securities, grouped into 14,315 deals, which were issued between January 2000 and December 2010. We consider, as our main measure of performance at the deal level, the deal value-weighted percentage of securities that are classified in default by a rating agency. Furthermore, we adopt two measures of reputation at the underwriter level: one based on the prominence of banks that participate in initial public offerings of equities and one based on the ranking of underwriters in fixed income league tables.

The most central empirical prediction of the model is that high-reputation underwriters can have an incentive to create complex securities that perform worse through a crisis. Interestingly, we find that high-reputation underwriters issued securities that did not outperform and, in fact, typically underperformed securities issued by low-reputation underwriters. The underperformance occurred in the crisis years of 2007, 2008, and 2009, as well as in the mini structured finance crisis of 2002; it is prominent in the MBS, ABS, and CDO markets and is robust to both measures of reputation. The results hold both unconditionally and with controls and vintage-by-collateral-type fixed effects, indicating that these underwriters produced poor securities within the MBS, ABS, and CDO markets. Our findings are not driven by observable underlying asset quality or features associated with complexity, such as synthetic collateral and various forms of credit enhancements. They are not unique to residential housing mortgages and are not related to the presence of Bear Stearns and Lehman Brothers in our sample. For a subset of prime and subprime nonagency MBS for which detailed collateral information is available, we find that high-reputation underwriters collateralize slightly more concentrated loans (in California), less subprime and more Alt-A, and exhibit poor abnormal loan performance. Nevertheless, these features cannot completely explain why MBS securities produced by high-reputation underwriters had significantly more capital in default than similar securities produced by low-reputation underwriters.

Overall, after adjusting for observable characteristics, securities produced by high-reputation underwriters were sold at similar issuance yields-to-maturity to those created by low-reputation underwriters. Thus, investors were not able to anticipate the subsequent difference in performance. Moreover, controlling for perceived riskiness, as measured by yields, does not impact the negative relation between performance and reputation.

Our second main prediction is that strategic underwriters, including those with a good reputation, may push securities to the market even in the period prior to an impending collapse. They do so because creating each security is quite profitable and they know that their perceived good reputation will be lost once the downturn occurs and the previously created bad securities are revealed. From various public documents regarding the increase in mortgage delinquencies, it seems likely that underwriters were aware at least by the early months of 2007 that the quality of mortgage-related collateral was deteriorating. Nevertheless, issuance volume by high-reputation players in the first half of 2007 was nearly identical to that in 2006. This finding could be consistent with the results put forth by Titman and Tsyplakov (2010), who find that commercial mortgage originators packaged worse collateral following large negative stock returns in the prior quarter. However, in contrast to this explanation, we find that the underperformance of securities from high-reputation underwriters is not limited to securities produced in crisis years but comes from securities issued across seven of the eleven years in our sample. Additionally, controlling for past stock returns or CDS spreads of the issuing bank does not dampen the negative relation between high reputation and performance.

Finally, we examine the possibility, allowed by our model, that some high-reputation underwriters were committed to producing high-quality securities. We test this by examining whether a bank with high reputation both produced high-quality structured products and withdrew from the market in 2007. We do not find high-reputation banks with more than a few issuances that meet this criteria.

Some recent theory papers, like ours, challenge the conventional intuition about the inherent disciplining effect of reputation, though our focus is significantly different. Mathis, McAndrews, and Rochet (2009) and Fulghieri, Strobl, and Xia (2014) argue that rating agencies may find it convenient to strategically build and then burn their reputation. Similarly, in the context of issuance, Hartman-Glaser (2012) develops a model in which high reputation leads to frequent misreporting of the true value of an asset when issuers also have the opportunity to signal quality through retention. More closely related to our focus, Chen, Morrison, and Wilhelm (2012, 2014) study the interaction between the concern that firms and banks have for maintaining a reputation for honesty and the concern employees in banks have to develop a reputation for skill. Also in the context of investment banking, Morrison and Wilhelm (2004, 2008) note the recent demise of an organizational structure in which investment bank partnerships allow a long-run firm to use its reputation to commit to monitoring and training employees. Differently from these studies, we address the incentives to actively produce low-quality securities.

From the empirical side, there are a number of recent papers examining structured finance. Keys et al. (2010), Purnanandam (2011), Keys, Seru, and Vig (2012), and Nadauld and Sherlund (2013) find that poor incentives, tied to the "originate-to-distribute" model, lead to declining securitization standards. Ashcraft, Goldsmith-Pinkham, and Vickery (2010), Mayer, Pence, and Sherlund (2009), and Demyanyk and Van Hemert (2011) give a thorough documentation of the performance of housing mortgages and the erosion in loan quality starting in 2004 and lasting throughout the crisis.[1] Piskorski, Seru, and Witkin (2013) and Griffin and Maturana (Forthcoming) find evidence of mortgage misreporting in nonagency MBS by both originators and underwriters; this misreporting was not priced by investors at issuance and yet strongly predicted future MBS losses. Nadauld and Weisbach (2012) and Ivashina and Sun (2011) show that securitization lowers the cost of corporate debt. We extend this literature by examining the important role that bank reputation may or may not have played as a disciplining mechanism in the period leading to the financial crisis. We focus on the incentives of those supplying securities and not the determinants of credit demand as recently explored by Erel, Nadauld, and Stulz (2014) and Chernenko, Hanson, and Sunderam (2014).

Our findings at first seem contradictory to a large body of literature showing the value of investment bank reputation in the IPO (Beatty and Ritter 1986; Carter and Manaster 1990; Lewellen 2006), bond (Fang 2005), loan (Ross 2010), and acquisition markets (Golubov, Petmezas, and Travlos 2012). However, our model shows that with simple assets, such as corporate debt, where investors can use accounting information to discern if the underwriter misrepresented the securities, high reputation should lead to higher quality securities even if high-reputation underwriters are not, in fact, committed to investors' interests. In contrast, with complex securities the true quality of the security is not revealed until the bad state occurs. This can potentially explain why our empirical findings for structured products widely differ from these other studies that analyze simpler securities.

We believe our paper makes an important and timely contribution to the understanding of the role that underwriter reputation may have played in issuance of financial products that crippled our financial system. Our research should be of interest to investors, regulators, bankers, or anyone seeking to understand the incentives of bankers and the complexity of securities they create.

1. Model and Empirical Predictions

We consider an over-the-counter market for structured products, where a single underwriter faces a single investor in each period. The economy has two

[1] He, Qian, and Strahan (2014) found that large issuers had to offer higher yields than did small issuers, suggesting that the market was aware that these large MBS issuers received more inflated ratings.

states, a normal state, occurring with probability $\pi > \frac{1}{2}$, and a disaster state. The underwriter produces a security that he then sells to the investor. The security is produced before the state is realized and has a payoff that will depend on the realized state. We assume some exogenous gains to trade between the investor and the underwriter, such that the investor values the security more than the underwriter. Furthermore, because the security is a structured product, the underwriter has some ability to select the payoff profile across economic states.

Specifically, we assume that the underwriter may pay a cost to provide to the investor some level of insurance, which increases payoffs in the bad state at the expense of payoffs in the good state: for example, in the case of structured finance, insurance can be achieved by collateralizing assets/securities that have low correlation. Alternatively, the underwriter can investigate the pool of assets and select those that are highly correlated, thus creating a security that provides "negative insurance." The investor dislikes this second security as it has lower payoff in the bad state. We represent the level of insurance (correlation) provided to the investor as $w \in (-\infty, \infty)$, where $w > 0$ is positive insurance (low correlation) and $w < 0$ is negative insurance (high correlation).[2] The cost of analyzing and selecting the assets to include in the collateralized security is w^2. Thus, providing negative insurance is Pareto dominated in the stage game. As we will show, however, this action can allow the underwriter to disguise the magnitude of the markup charged to the investor.

The underwriter is also assumed to have better information about the overall quality of the security pool. The underwriter can choose to sell the security to the investor at a "fair" price or at a markup above the fair value. That is, defining the fair value of the security as v, the underwriter selects a price p, which then gives a markup $(p-v)$. We define $\theta \equiv 1-(p-v)$ and let the underwriter choose $\theta \in [0,1]$, where θ represents the level of truthfulness. Simultaneously to the production and pricing decision, the investor chooses a quantity of the security to purchase, $y \in [0,2]$.[3] The total payoff given w, θ, and y for each player (u for underwriter and I for the investor) is given by

$$g_u(p-v, w, y) = y\left(a+(p-v)-w^2\right)$$

$$g_I(p-v, w, y) = y(b+w-(p-v)) - \frac{1}{2}y^2.$$

As described, the investor's payoff is increasing in the level of insurance provided and decreasing in the markup. The parameters a and b represent the exogenous gains to trade shared between the underwriter and the investor,

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2 Our results will also hold with a more microfounded model of security design, but we take the reduced-form approach described here to keep the analysis simple and to focus on the role of reputation.

3 As is standard in models of over-the-counter trading, we assume the investor is not holding a fully diversified portfolio of all assets in the economy and thus faces some risk associated with the particular security he is purchasing. We represent this with a quadratic cost for securities.

respectively. The investor's total payoff is the average payoff over the two states, where in each state the payoff is:

$$g_I^h(p-v,w,y)=y(b+\eta-(p-v)-w)-\frac{1}{2}y^2$$

$$g_I^l(p-v,w,y)=y\left(b+\frac{1+\pi}{1-\pi}w-(p-v)-\frac{\pi}{1-\pi}\eta\right)-\frac{1}{2}y^2$$

where h and l represent the payoff in the normal and disaster state, respectively. The parameter η, which drops out when averaging across the states, represents the exogenous change in the value of the security in response to general market conditions.

The security produced by the underwriter is complex in the sense that the investor can only observe the realized payoff in the state that occurs but cannot infer the level of insurance provided and the magnitude of the markup. Hence, the realized payoff in one state is not informative about what the realized payoff of the security would be in the other state. Alternatively, when securities are simple, investors can perform a counterfactual analysis of the state payoffs. An example of this type of security is a corporate bond, where accounting data would potentially provide enough information about firm performance to allow an investor to evaluate whether the firm would have likely defaulted in a recession, even if the recession is not observed.[4]

We impose that the exogenous division of the gains to trade (i.e., the choice of a and b) is either sufficiently even, or that the absolute level of gains to trade available to the underwriter (a) is not too large relative to the effect of insurance provision (w) and the effect of truthfulness (θ) on the payoff to the underwriter. Hence, in this section, we focus on a convenient normalization by setting $a=\frac{5}{4}$ and $b=\frac{3}{2}$. These parameters are selected so that a and b are sufficiently large to allow the market to operate even in the absence of commitment types, and further so that a will not be too large relative to b. As we show in the Internet Appendix, if a becomes very large relative to b, the underwriter's actions become largely payoff irrelevant to the underwriter, and the region over which reputation provides bad incentives shrinks.

We allow for the presence of two pools of underwriters: one pool, which we will refer to as the high-reputation group, includes a proportion μ of underwriters that are committed to provide the efficient level of insurance ($w=\frac{1}{2}$) and the most truthful strategy possible ($\theta=1$).[5] Because the investor

[4] Some investors in structured products (like hedge funds) may also be sophisticated modelers, but they are typically not able to access the same level of detailed underlying asset information available to the underwriter.

[5] We note here that having the price set by the commitment type will in effect pin down the price charged for all securities. Therefore, prices will in a sense not respond to investors' equilibrium beliefs about the behavior of strategic players or the fraction of commitment types in the economy. Our main results are robust to an alternative setting in which commitment types adjust their behavior to reflect the ex ante expected payoff from dealing with a reputable underwriter relative to a low-reputation underwriter.

does not know which underwriter is committed, he attaches a probability of commitment μ to each one of them, which is the source of the "high reputation." We will refer to the underwriters that are not committed but belong to the high-reputation group as the strategic high-reputation underwriters. These underwriters always pursue their own profits but will at times have an incentive to temporarily forgo current profits to maintain their reputation for the future. The second pool, which we will refer to as the low-reputation group, is composed of underwriters that are known to be concerned only about their own profits and have therefore zero commitment probability.

The notion of a commitment type who forgoes profit maximization is a relatively standard definition of reputation and follows Milgrom and Roberts (1982) and Kreps et al. (1982), where there is uncertainty over whether a long-lived player maximizes his own utility or commits to a particular set of actions.[6]

We allow the interaction to repeat twice, assume no discounting between periods, and note that a sufficiently high discount rate will undo the incentives for strategic underwriters to try to appear to be commitment types. When discounting is too strong, underwriters will have no incentive to preserve their reputation no matter its initial level, and only the direct effect of encountering a commitment type will differentiate high-reputation and low-reputation underwriters.

Our main analysis is concentrated on understanding the (first-period) equilibrium strategies of investors and underwriters. We compare the effect of reputation on underwriter behavior when securities are complex, as would be the case with structured products, against the effect when securities are simple. All proofs for these results, along with some further discussion of the intuition underlying the results, can be found in the Internet Appendix.

When securities are simple, the standard result in reputation models holds.[7] A reputation itself is sufficient to discipline behavior by high-reputation strategic players. Furthermore, investors are better off when underwriters have high reputation, even when they turn out to not be a commitment type: the higher the probability of facing a commitment type gets, the better off the investor is.

This result is summarized in the following proposition:

Proposition 1. With $a=\frac{5}{4}$ and $b=\frac{3}{2}$, when a strategic underwriter has a high reputation, such that $\mu \geq \frac{20}{27}$, the unique equilibrium of the game with simple securities is for the strategic underwriter to fully imitate the commitment type in the first period and then use the stage game equilibrium in the second period by playing the myopic best response of $w=0, \theta=0$. Furthermore, if $\mu < \frac{20}{27}$, the

[6] Similar predictions can be generated with a more complex model, which was analyzed in a previous version of the paper, where no commitment types are assumed and low-reputation underwriters focus on short-term profits whereas high-reputation underwriters focus on long-term profits.

[7] The investor has access to information that allows him to observe both θ and w or, equivalently, can perform a counterfactual analysis of the payoffs that would have occurred in the state that was not realized.

probability that the strategic underwriter creates commitment type securities is increasing in the commitment probability.

In contrast, for complex products for which investors cannot recover good estimates of counterfactual payoffs, as long as $\mu > 0$, there is an incentive and an opportunity for strategic underwriters to take advantage of their reputation and produce securities that maximize their profits at the expense of delivering a poor performance to the investor when the disaster state is realized (a sort of "time bomb" security).

We proceed by discussing two approaches to analyzing our reputation model. First, as is common in recent applied work on reputation in finance (e.g., Fulghieri, Strobl, and Xia 2014), we treat the probability of encountering a commitment type as a parameter and consider the effect of changes in the parameter on the behavior of a strategic player. Second, following the tradition in the game theory literature, we focus on comparisons between players known to be short-term profit maximizers (i.e., that have zero probability of being committed) and players who have a small probability of commitment to a particular strategy (e.g., Kreps et al. 1982; Milgrom and Roberts 1982).

1.1 The behavior of high reputation strategic players

A strategic player with high reputation will find it advantageous to produce securities that result in the same payoffs as securities produced by commitment types in good states of the world but have very poor performance in bad states of the world. This is achieved by choosing $\theta = 0$ and $w = -\frac{1}{2}$. Notably, this strategy is still profitable for underwriters, as the markup over fair price is at its maximum, although it is not as profitable as the stage game strategy that has maximum markup and zero cost ($\theta = 0, w = 0$). However, this "time-bomb" security is not produced with probability one. In fact, there exist many possible equilibria. Depending on the level of μ, a strategic underwriter might play a mixed strategy, sometimes fully imitating commitment-type behavior and sometimes generating time bombs. For a choice of $a = \frac{5}{4}$ and $b = \frac{3}{2}$, equilibrium strategies played by a strategic player are displayed in Figure 1, panel A, as a function of possible combinations of the probability of the normal state, π, and of the commitment probability, μ. For the smallest values of μ, the probability of encountering a commitment type is low and underwriters mostly mix between the myopically optimal security ($\theta = 0$ and $w = 0$) and the time bomb security ($\theta = 0$ and $w = -\frac{1}{2}$). For higher values of μ, underwriters mix instead between a high probability of building the time bomb security and a small probability of creating the full commitment security.[8]

Figure 1, panel B, displays the relation between the probability of a time bomb from a strategic underwriter and the commitment-type probability μ for

[8] In the white region near the y-axis, multiple equilibria hold over part of the region; details are in the Internet Appendix.

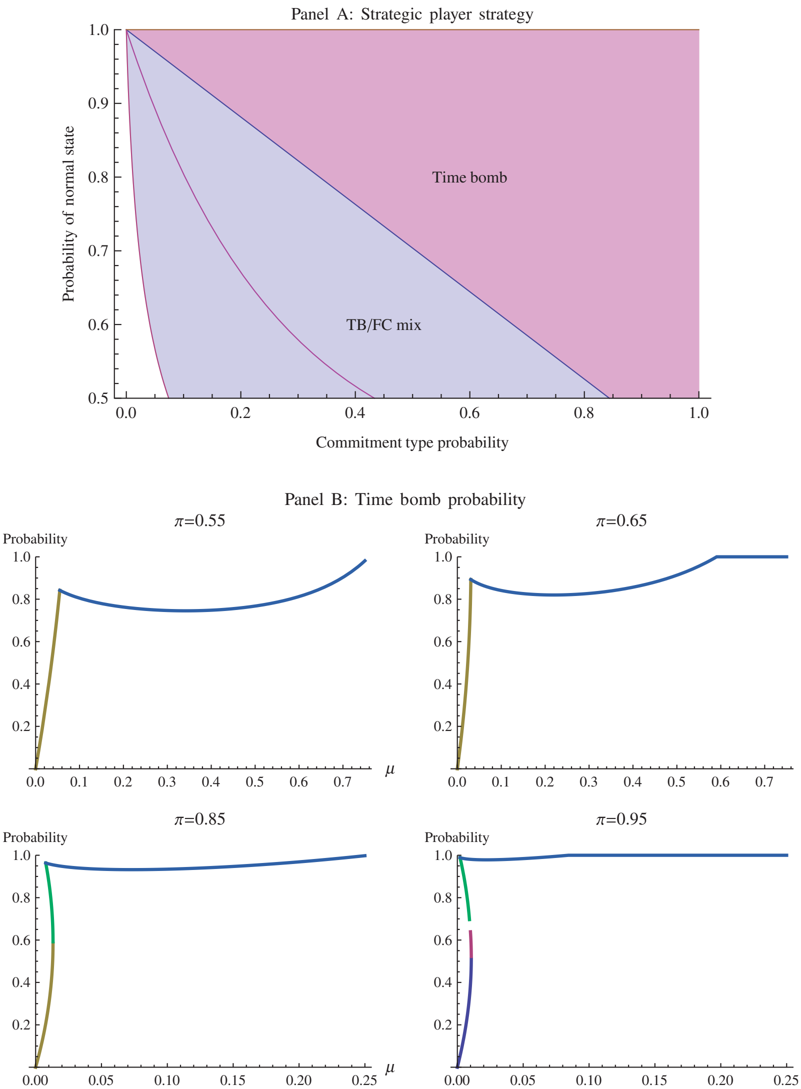


Figure 1
Model equilibria
This figure shows the equilibrium strategy of a strategic player with a positive commitment probability in the case in which $a=5/4$ and $b=3/2$. In panel A, we show the possible equilibria for all possible combinations of the probability of the normal state, π, and the commitment type probability, μ. The dark region represents the area in which the strategic underwriter only produces time bombs. The light region represents the combination of parameters for which the equilibrium of the strategic underwriter is a mixed strategy of time bombs and full-commitment-type securities. In panel B we plot the probability that a strategic underwriter produces a time bomb security as a function of μ, for four possible probabilities of the normal state ($\pi=\{0.55, 0.65, 0.85, 0.95\}$).

selected values of the normal state probability.[9] For $\pi \leq \frac{2}{3}$ (e.g., the top two panels of the figure), the equilibrium is unique for all values of μ. As μ increases away from zero, the probability of a time bomb increases sharply, with the strategic underwriter mixing among all three security types. The probability of a time bomb then drops slightly as the underwriter begins to mix only between time bombs and the full commitment strategy, and finally increases again until it reaches one.

For higher values of π (i.e., bottom two panels of the figure), there are multiple equilibria when μ is small, making a clean comparative static impossible. It is still the case that the probability of a time bomb is increasing over small values of μ. As μ increases, we still observe a region in which the time bomb probability decreases; however, the reduction becomes trivial. In the case in which the disaster state is most rare (for example, $\pi = 0.95$), which is arguably the parameter range of interest, a higher commitment probability most generally leads to a greater likelihood of a time bomb from the strategic underwriter.

1.2 Security expected payoff

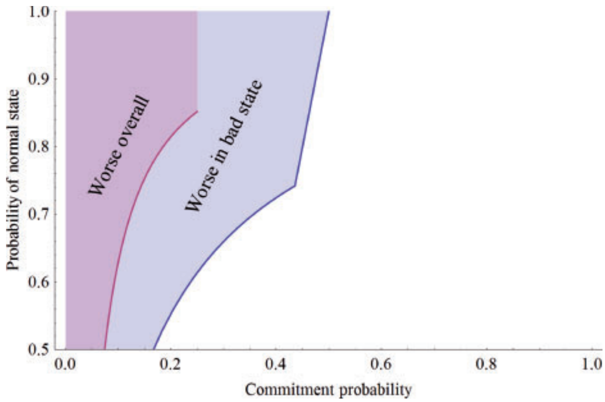
We compare the security's expected payoff (i.e., $b+w-(p-v)$) for the case in which the investor is matched to an underwriter with low reputation relative to the case in which he is matched to a high-reputation underwriter who is drawn from a pool including a small number of commitment types. The low-reputation underwriter, who is known to have zero probability of being committed, always chooses $\theta = 0$ and $w = 0$, the myopically optimal security (i.e., the security that maximized the first period profits). When the investor is matched to a high-reputation underwriter, he will meet a strategic player with probability $1-\mu$ and a committed player, who always provides the efficient level of insurance ($w = \frac{1}{2}$) and the most truthful strategy possible ($\theta = 1$), with probability μ.

In Figure 2, panel A, we display the result of the analysis for different levels of the normal state probability, π, and of the commitment probability, μ. For some parameter values of interest, the expected payoff to the investor is worse when facing an underwriter with a positive probability of being a commitment type than it would be if the underwriter were known to be a strategic short-term profit maximizer. If the fraction of committed underwriters is small, the incentives of strategic players with a reputation are bad enough to overwhelm the value created by the true commitment types. In particular, in the dark region the investor is always better off dealing with the low-reputation strategic player that is only maximizing profits. In the light region, the investor is worse off facing a pool of underwriters that contain some commitment types if the bad state of nature is realized.

This effect is quite strong; the probability of facing a commitment type must get quite high before reputation becomes value creating rather than value

[9] Proposition 7 in the Internet Appendix formalizes the comparative static argument described here.

Panel A: Expected payoff when dealing with high relative to low reputation underwriter



Panel B: Expected investor payoff for certain values of the normal state probability

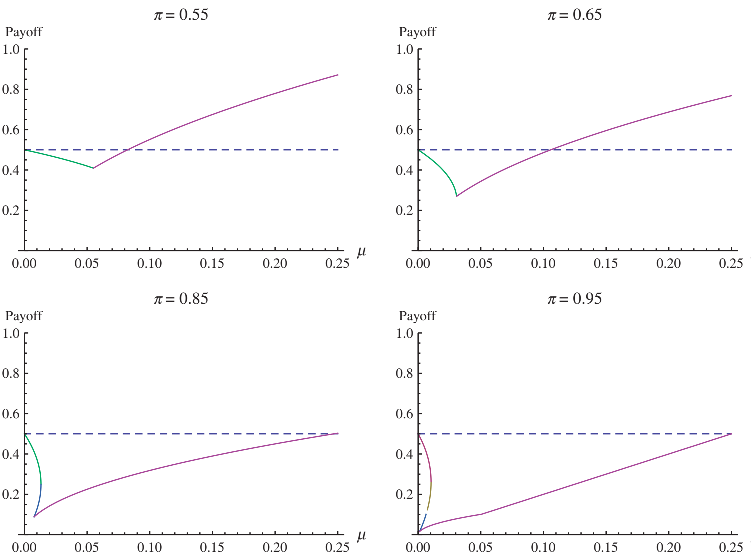


Figure 2
Expected investor payoff and reputation
These figures plot the expected investor payoff, in the case in which $a = 5/4$ and $b = 3/2$, as a function of model parameters for an investor when dealing with a high-reputation underwriter ($\mu > 0$). In panel A, we show how the investor fares when dealing with a player that might be a commitment type, relative to the case in which the investor faces a strategic player that is purely profit maximizing (low reputation, $\mu = 0$), as a function of the commitment probability (μ) and the probability of a normal state (π). In the white region the investor is always better off facing a pool of underwriters that contain some commitment types. In the dark region the investor is always better off dealing with the strategic player that is only maximizing profits. Finally in the light region, the investor is worse off facing a pool of underwriters that contain some commitment types if the bad state nature is realized. In panel B we plot the expected payoff of an investor when dealing with a commitment type as a function of the probability that the underwriter is a true commitment type, for four possible probabilities of the normal state ($\pi = \{0.55, 0.65, 0.85, 0.95\}$). The dotted line is the payoff from dealing with a low-reputation underwriter ($\mu = 0$). The remaining lines summarize the possible payoffs from dealing with a high-reputation underwriter ($\mu > 0$) as a function of μ. Note that the payoff for a given level of μ is not unique because in some regions there are multiple equilibria.

destroying from an ex ante perspective. The reason for this is that, at the margin, an increase in the probability of facing a commitment type increases the incentives of the strategic type to produce "time bombs," offsetting the perceived benefit of being more likely to face a true commitment type.

Figure 2, panel B, displays the relation between expected payoffs and commitment-type probability for selected values of the normal state probability. The negative effect of reputation arises rapidly as the probability of a commitment type increases away from zero. Moreover, the fraction of commitment types required to offset the action of strategic players is increasing with the probability of a normal state. When the disaster state is particularly rare ($\pi = 0.95$), the investor is better off facing a low-reputation underwriter unless the fraction of high-reputation underwriters who are commitment types is particularly large (i.e., larger than 25%).

We summarize this result in the following proposition:

Proposition 2. With $a = \frac{5}{4}$ and $b = \frac{3}{2}$, as long as $\mu < \min\left\{\frac{1}{4}, \frac{1}{27}\frac{1}{1-\pi}\right\}$, the expected payoff from the security is lower than when dealing with an underwriter who is known to be fully strategic ($\mu = 0$). Furthermore, if $\min\left\{\frac{1}{4}, \frac{1}{27}\frac{1}{1-\pi}\right\} < \mu < \min\left\{\frac{1+\pi}{4}, \frac{(1+\pi)^2}{27(1-\pi)}\right\}$, investors prefer to deal with a reputable underwriter.

In summary, the expected performance of securities created by an underwriter with small commitment probability might be worse than the performance of securities created by a player that is known to be a short-term profit maximizer. Moreover, a negative relationship between reputation and quality of securities also can be obtained in the case in which the investor's beliefs about the proportion of committed underwriters are misplaced. If it turns out that all underwriters are in fact strategic, our analysis on the behavior of high-reputation strategic underwriters suggests not just that a high reputation may lead to worse performance but also that the higher the belief about the commitment probability, the worse the performance will be. This type of conjecture breaks the link between the prior commitment-type probability used by investors and the realized, true composition of the population. Such a disconnect between the ex ante probability of commitment and the realized, ex post fraction of players who truly are commitment types is not necessarily an indication of irrational beliefs by investors; it is likely that there will be significant correlation in the incentives facing underwriters that will lead some to behave as commitment types. Thus, the probability of high-reputation underwriters being commitment types could be interpreted as the probability that all high-reputation underwriters are jointly commitment types, because the factors that determine whether an underwriter is truly committed to investors may be common across all underwriters. That is, if the realization of whether high-reputation underwriters are commitment types is highly correlated, it would not be surprising that the ex ante prior on the commitment type probability does not match the actual distribution of commitment types.

1.3 Hypotheses

Our model shows why reputation may provide bad, rather than good, incentives to strategic underwriters in the market for complex products. These results suggest that, in contrast with other markets, we could detect underperformance by high-reputation underwriters, particularly during bad economic states. This implication contrasts with most other findings, both empirical and theoretical, on the effect of reputation on the quality of securities issued.

Hypothesis 1. Securities produced by low-reputation underwriters will outperform securities produced by high-reputation underwriters in a crisis period and will be indistinguishable in non-crisis periods.

To supplement this main hypothesis, we also consider how the high-reputation strategic underwriters will behave once it becomes apparent, to them at least, that the realization of the bad state is imminent. Once the disaster state is realized, the strategic underwriters will be revealed as having produced poorly performing securities. Hence, because each new deal is extremely profitable, the underwriter will continue to issue securities that will blow up. This leads to our second empirical hypothesis:

Hypothesis 2. High-reputation underwriters will not voluntarily decrease the volume of issues in the period immediately prior to the crisis.

2. Data and Reputation Measure

2.1 Data

We collect issuance and rating history data for all nonagency-structured finance securities issued from January 2000 through December 2010 that are available on the Bloomberg system. The data are broadly classified as collateralized loan obligations (CLO), nonagency mortgage-backed securities (MBS), asset-backed securities (ABS), and collateralized debt obligations (CDO), where CDOs are generally defined as collateralized debt securities backed by MBS, ABS, and other CDO securities. Therefore, CLO, MBS and ABS arise from a first round of securitization of individual debt claims, whereas CDOs arise from a second round of securitization, also known as repackaging.

In this spirit, we order the data in this manner (CLO, MBS, ABS, and CDO) because we believe that this reflects an increasing order of collateral complexity. The collateral pool of a CLO is typically composed of 50 to 100 corporate loans that usually come with enough detailed information to make possible a partial assessment of the quality of the loans. Because of the high level of transparency, we include collateralized corporate bond obligations, CBOs, in the CLO group.

In contrast to CLOs, MBS and ABS are usually composed of thousands of individual claims whose original debtor is either a physical individual or a small legal entity (in the case of CMBS). MBS consists of both residential (RMBS) and commercial mortgages (CMBS) that are largely outside of the standards for securitization used by the government sponsored enterprises. We do not examine agency RMBS because they are implicitly guaranteed by the government. Nonagency RMBS consists of prime, first-lien fixed, Alt-A, and adjustable rate loans. ABS consists of auto loans, credit card loans, equipment, home equity, manufactured housing, student loans, and other.[10] ABS Home Equity is distinct from MBS because it contains various forms of nonstandard residential housing debt, including subprime, home equity, and second-lien loans.

It would be difficult to check the quality of each mortgage supporting an MBS, and, therefore, investors likely must rely on reported summary statistics. For ABS securities, in addition, the collateral is typically less standardized (i.e., auto loans, credit cards receivables, and subprime mortgages), making it even more difficult to perform an effective valuation, not to mention an accurate assessment of the pool correlation structure. Finally, we reserve our CDO category for collateral obligations constructed using an asset that is from another structured finance product (ABS, MBS, or another CDO). CDOs would be relatively hard to evaluate because they are at least one more step removed from the underlying asset.

We collect information at the security level and then aggregate all securities that are backed by the same collateral pool into one financial structure, which we refer to as a "deal." In our empirical analysis we lose some (mostly MBS) deals because ratings are not available or the underwriters do not have a reputation measure (which we detail in the next section). Table 1 reports summary statistics for the sample of 14,315 deals that are used is our analyses. The sample is comprised of 132,401 securities (tranches) worth \$10.1 trillion at issuance. From Panel A, we learn that the collateral is most concentrated in the nonagency residential MBS at \$4.9 trillion. ABS consists of \$3.9 trillion with \$2.2 trillion from Home Equity (the majority of which are comprised of subprime mortgages). The CLO and CDO categories are considerably smaller and similar to each other in size. The structured finance CDOs consist of \$659 billion, with the majority of the collateral from ABS. Internet Appendix Table A.1 details these issuance figures by subcategories through time. The average deal size for each category is typically over 714 million USD with both residential and commercial MBS having an average size of around \$1 billion dollars. Across collateral types, at least 70% of the capital that comprises a deal is rated

[10] Some of the student loans that are found in the collateral pool of student loan ABS in fact carry a guarantee by the Department of Education, which was enforced through various government related entities (Sallie Mae being one of them). Because the guarantee was not for 100% of the value of the loan, and because of the difficulty in distinguishing between securities backed by loans issued under FFELP and private loans, we leave student loans ABS in the sample.

Table 1
Summary statistics

Panel A: Deal characteristics

	TOTAL	CLO				MBS (Nonagency)		
	CLO, MBS, ABS, CDO	Loan	Bond	TP	Total	RMBS	CMBS	Total
Number of deals	14,315	984	228	52	1264	3981	686	4667
Number of securities	132,401	6269	1042	435	7746	58531	9373	67904
Average deal size (M)	714.9	598.9	280.4	507.9	537.7	1060.6	1081.1	1063.6
Average maturity	25.3	15.2	11.5	31.2	15.2	32.4	24.5	31.2
Average rating	2.6	2.1	2.6	2.5	2.2	1.8	2.4	1.9
Proportion of AAA	0.704	0.733	0.624	0.638	0.709	0.855	0.747	0.839
Underwriter reputation	8.6	8.6	8.5	8.7	8.6	8.5	8.6	8.5
Proportion of IB	0.570	0.582	0.803	0.558	0.621	0.561	0.672	0.577
Total amount (B)	10,233.5	589.3	63.9	26.4	679.7	4222.3	741.6	4963.9

	ABS								CDO				
	Auto	Credit card	Equip.	Home equity	Manuf. housing	Student loan	Other	Total	ABS	MBS	CDO2	Missing	Total
Number of deals	595	910	121	3,952	75	102	1,194	6,949	676	137	96	526	1,435
Number of securities	2,490	1,605	529	40,191	542	428	3251	49,036	3,892	1,093	572	2,158	7,715
Average deal size (M)	884.1	696.1	494.5	565.2	352.4	805.7	308.6	565.6	590.2	554.7	347.6	287.8	459.8
Average maturity	7.4	7.6	9.1	29.7	30.7	29.7	15.5	22.1	35.8	38.1	31.1	20.2	30.0
Average rating	1.5	2.7	1.7	3.6	2.3	1.3	3.1	3.1	2.2	3.2	2.4	3.2	2.6
Proportion of AAA	0.807	0.727	0.764	0.594	0.751	0.922	0.550	0.631	0.701	0.581	0.659	0.490	0.609
Underwriter reputation	8.6	8.7	8.3	8.5	8.6	8.7	8.5	8.6	8.5	8.3	8.6	8.6	8.5
Proportion of IB	0.508	0.567	0.331	0.603	0.693	0.745	0.459	0.564	0.481	0.526	0.552	0.591	0.530
Total amount (B)	526.0	633.5	59.8	2,233.7	26.4	82.2	368.5	3,930.1	399.0	76.0	33.4	151.4	659.7

Panel B: Complexity characteristics

	TOTAL	CLO				MBS (Nonagency)		
	CLO, MBS, ABS, CDO	Loan	Bond	TP	Total	RMBS	CMBS	Total
Collateral account	0.007	0.009	0.005	0.000	0.008	0.001	0.000	0.001
Cross collateralization	0.058	0.000	0.000	0.000	0.000	0.081	0.000	0.068
Insurance	0.069	0.036	0.087	0.059	0.046	0.025	0.003	0.022
Letter of credit	0.002	0.001	0.000	0.000	0.001	0.000	0.000	0.000
Overcollateralization	0.245	0.053	0.214	0.000	0.077	0.064	0.014	0.056
Reserve account	0.088	0.062	0.026	0.118	0.059	0.032	0.015	0.029
Apread account	0.182	0.009	0.005	0.000	0.008	0.067	0.005	0.057
Subordination	0.465	0.615	0.204	0.667	0.550	0.321	0.048	0.277
Synthetic collateral	0.038	0.021	0.296	0.000	0.065	0.000	0.000	0.000

	ABS								CDO				
	Auto	Credit card	Equip.	Home equity	Manuf. housing	Student loan	Other	Total	ABS	MBS	CDO2	Missing	Total
Collateral account	0.025	0.056	0.000	0.001	0.000	0.010	0.003	0.011	0.002	0.000	0.000	0.005	0.003
Cross collateralization	0.004	0.000	0.000	0.130	0.028	0.082	0.002	0.076	0.000	0.000	0.000	0.000	0.000
Insurance	0.122	0.032	0.092	0.140	0.181	0.134	0.090	0.115	0.020	0.040	0.012	0.020	0.022
Letter of credit	0.035	0.001	0.000	0.000	0.014	0.021	0.005	0.004	0.000	0.000	0.000	0.000	0.000
Overcollateralization	0.475	0.027	0.316	0.641	0.736	0.278	0.074	0.440	0.072	0.064	0.073	0.040	0.061
Reserve account	0.645	0.234	0.653	0.025	0.056	0.588	0.154	0.148	0.007	0.008	0.012	0.028	0.015
Apread account	0.277	0.178	0.255	0.466	0.194	0.361	0.051	0.336	0.005	0.000	0.000	0.003	0.003
Subordination	0.626	0.722	0.602	0.610	0.472	0.557	0.218	0.564	0.575	0.712	0.500	0.301	0.490
Synthetic collateral	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.286	0.088	0.390	0.412	0.315

Panel C: Percentage of deal in default as of December 2010

	Mean	25*th*	50*th*	75*th*	90*th*
Overall	0.306	0.000	0.024	0.705	1.000
Total CLO	0.120	0.000	0.022	0.068	0.422
Loan	0.051	0.000	0.018	0.049	0.092
Bond	0.311	0.000	0.000	0.920	1.000
TP	0.577	0.318	0.493	1.000	1.000
Total MBS	0.277	0.000	0.021	0.570	1.000
RMBS	0.309	0.000	0.026	0.766	1.000
CMBS	0.094	0.000	0.000	0.058	0.243
Total ABS	0.303	0.000	0.000	0.642	1.000
Auto loans	0.008	0.000	0.000	0.000	0.000
Credit card	0.014	0.000	0.000	0.000	0.000
Equipment	0.074	0.000	0.000	0.000	0.000
Home equity	0.437	0.000	0.320	1.000	1.000
Manufactured house	0.360	0.000	0.184	1.000	1.000
Student loans	0.056	0.000	0.000	0.000	0.083
Other	0.266	0.000	0.000	1.000	1.000
Total CDO	0.573	0.000	1.000	1.000	1.000
ABS	0.758	0.336	1.000	1.000	1.000
MBS	0.467	0.052	0.272	1.000	1.000
CDO2	0.640	0.137	1.000	1.000	1.000
Missing	0.352	0.000	0.000	1.000	1.000

This table reports summary statistics for issuances of CLO, MBS, ABS, and CDO securities from January 2000 through December 2010. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. In panel A, we present the total number of deals, the total number of securities (tranches), the average deal size (in million USD), the average stated maturity, the average rating at issuance, the average of the value-weighted proportion of AAA-rated tranches within each deal, the average underwriter reputation score, the proportion of deals from an investment bank, and the total amount of issuance (in billion USD). (Year-by-year issuance volumes are available in Internet Appendix Table A.1.) In panel B, we report the proportion of deals that have a credit enhancement or synthetic collateral. There are eight forms of credit enhancements that are reported in our data: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. In panel C, we report the empirical distribution of the proportion of deal in default as of the end of December 2010. Ratings are converted into a numeric scale using standard conventions: AAA = 1, AA+ =2, ..., D = 21. For each market (i.e., CLO, MBS, ABS, and CDO), we present disaggregated results based on the type of collateral that is (predominantly) backing the deals. The data are from Bloomberg.

AAA at issuance. RMBS, auto loans, equipment, and student loans have as much as 80% of their securities rated AAA at issuance. Fifty-seven percent of the deals are created by investment banks.[11] In panel B, we report the proportion of deals that have a credit enhancement or synthetic collateral. There are eight forms

[11] We have collected industry classification information for each underwriter from Bloomberg. Bloomberg classifies financial institution into ten main categories: Commercial Banks, Commercial Services, Diversified Operations, Finance-Commercial, Finance-Investment Banking, Institutional Brokerage, Advisory Services, Investment Management, Life Insurance, and Wealth Management. We classify Finance-Investment Banking and Institutional Brokerage as investment banks. This list includes Goldman Sachs, JP Morgan, Lehman Brothers and other smaller shops, for example, Warburg Dillon Read and William R. Hough. Examples of institutions that are not classified as investment bank are Chase Manhattan Bank, Citigroup, Commerzbank, Credit Lyonnais and others.

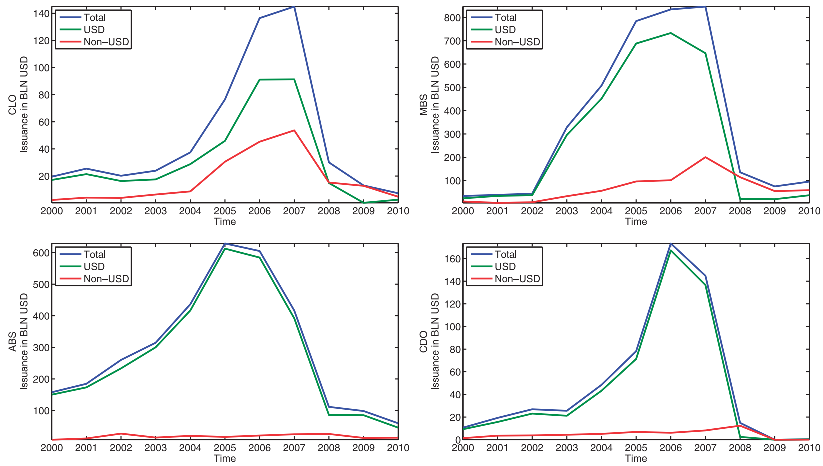


Figure 3
Amounts issued by year
This figure shows yearly issuance volumes (in billion USD) from January 2000 through December 2010. We report results separately for CLO, ABS, MBS and CDO securities. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. Deals denominated in non-USD currencies are converted into USD using the exchange rate current at the date of issuance. The data are from Bloomberg.

of credit enhancements that are reported in our data: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. Almost half of the deals have some form of subordination, whereas about a quarter have overcollateralization. The third most used form of credit enhancement is the presence of a spread account. However, there is a wide variability across each type of security in the use of any particular method of enhancement. Synthetic collateral is present only in CLO and CDOs and is the highest in CDO squared, ABS CDO, and Bond CLOs. We believe that our large dataset is unparalleled in breadth and should enable us to accurately test our main hypotheses.

Figure 3 shows the marked rise in issuance of structured products and the subsequent collapse following the onset of the financial crisis. The collapse in the market was most pronounced for the more complex ABS securities and structured finance CDOs. It is also interesting that most of the ABS and CDO markets are denominated in U.S. dollars, whereas the CLO market, and to a lesser extent the nonagency MBS market, have a more sizable non-U.S. component, which led to continued issuances in 2009 and 2010.

2.2 Reputation measure

We focus on reputation as a measure of whether a bank is committed to producing good securities. Ideally, we would evaluate reputation based on a bank's perceived overall reputation. We could consider issue volume, but there may be players in this market with high volume but low perceived reputation.

For example, Countrywide is the eleventh financial institution by issuance volume in our sample, but it had hardly any reputation outside of the mortgage origination business. The closest substitute that we identify is from the equity IPO market. We use a measure of underwriter prestige that is computed based on the original proposal of Carter and Manaster (1990): it gives a higher score to underwriters that appear more prominently on the tombstone of an IPO prospectus. Reputation scores for major players in the IPO market are available from 1984 through 2009 from Professor Jay Ritter's Web site.

Conceptually, we have in mind the idea that the reputation of a financial firm is shared across divisions. Underwriters who are understood to be focused on investors' interests, or at least longer-term profits, are exactly the underwriters with which a firm would like its IPO associated, based on the certification theory of investment banking (see, for example, Morrison and Wilhelm 2007). This measure has advantages because it is exogenous to decisions made in the market for structured products and can thus assess the prior beliefs about underwriters. Nevertheless, certain banks are considered stronger in either fixed income or equities, and thus the equity reputation may not perfectly correspond to the reputation in the fixed income space. However, there is no such direct relative prestige measure in fixed income.

Internet Appendix Table A.2 provides a list of all banks with their average (throughout the sample) reputation score as well as large banks without reputation scores.[12] Although the score is theoretically between 1 and 9, we are not sure that in practice there is much distinction captured by the difference between 8 and 9. As an example, highly regarded banks in 2006 and 2007, such as Lehman Brothers, Bear Stearns, Barclays Bank, and UBS have reputation scores of eight, whereas Credit Suisse and HSBC, for example, have a reputation score of nine even though they are arguably less well known or well regarded. For this reason, and to better align the empirical analyses with the theoretical setup discussed in Section 1, we group together banks with a score of 8 or 9 into a category labeled "High Reputation" and banks with a score lower than 8 into a group labeled "Low Reputation."[13] For deals that have more than one underwriter, the reputation score is calculated as the maximum score across underwriters.

The sample of deals for which we have an IPO reputation score is composed of 11,619 deals that account for 8.1 trillion USD of securities. Twenty underwriters have a reputation score of 8 or 9 and account for 95% of the volume: 5.1 trillion USD comes from banks with a score of nin, 2.6 trillion comes from banks with a score of eight. There are still 549 deals with a total of

[12] Because we average the reputation score through the sample, we consider in this table even deals produced by a bank for which we do not have a reputation score for the year in which the deal was issued. Therefore not all deals that appear in this table are necessarily used in all of the empirical analyses. The table is largely for expositional purposes.

[13] Internet Appendix Figure A.3 shows the distribution of issuances within the two groups: low-reputation underwriters issue proportionally less in the ABS market and more in the CDO market.

405 billion USD in capital represented by 21 institutions with a score of seven or less. There are about 2 trillion USD of securities that are issued by a bank without an IPO reputation score. Most of those banks are large and reputable European and Asian banks (e.g., Bank of Scotland, Royal Bank of Scotland, ABN Amro, Nomura International) that do not participate in the American IPO market and therefore do not have a score. Others are not as distinguished as the previous group. Because we do not want to make an arbitrary determination of what their reputation would be, we do not consider any of these banks in all our analyses that are based on the IPO reputation score.

As a way to mitigate the concern that we are omitting a significant part of the market and to offer an alternative to our main variable, we construct alternative reputation measures based on the overall market share of a bank in the entire fixed income space (League Ranking Tables). In particular, we construct two variables: the first is an indicator variable that is set equal to one for years in which a bank is ranked in the top ten (Top 10 League Rank). The second is the negative of the logarithm of the position in the table (League Rank). We use the logarithm to smooth out discrete differences, and we apply the negative sign to maintain a high value for high reputation. We use the league tables from the entire fixed income market, as opposed to structured finance, as a way to mitigate concerns of endogeneity (i.e., not to have the variable be too close to the focus of outcome choices of the banks participating in this market). The sample for which we have a reputation measure based on the league tables is composed of 13,669 deals that account for 9.8 trillion USD of securities.[14] Fifty-one percent of the sample (i.e., 5 trillion USD) belong to banks that are in the top ten of the league tables at any point in time; 2.3 trillion USD comes from banks between 11 and 25; and 2.5 trillion USD comes from banks between 26 and 500.

We note that the interpretation of our measurement of reputation requires care. The measures should provide an appropriate ordinal ranking of reputation and thus the likelihood that any given underwriter is a commitment type. The precise correspondence between the empirical reputation measures and the probability of commitment type behavior, however, is not obvious. Partly for this reason, we primarily focus on the implications of the model that compare known strategic types (low reputation) to underwriters with a small probability of commitment behavior (high reputation).

2.3 Performance measures

Rating changes rely on rating agencies, and research has questioned the accuracy of structured finance ratings. The event of default is typically a hard event tied to a violation of a covenant contained in the bond indenture (for example, an overcollateralization test). A tranche may fail to issue timely

[14] The total does not correspond to the number reported in Table 1 because there are underwriters with an IPO reputation score that do not appear in the League Tables.

interest payments and deal cash flows may be redirected toward higher priority tranches. With a hard event such as this, a rating agency might be forced to classify a tranche as in default, making this rating less subjective. Hence, as our main measure of performance, we consider the percentage of capital that receives a rating near default (Proportion of Tranches in Default).[15] The measure is constructed by calculating, at any point in time, the ratio of the nominal value of tranches that are in default to the total nominal value of the deal. Because rating agencies often do not report the last update when the security is in default, we consider securities with at least one rating below CC (Ca for Moody's) to be effectively in default.[16]

We measure deal performance by looking at the proportion of the deal in default as of December 2010. We report quartile distributions for the proportion of the deal in default for each category (CLO, ABS, MBS, and CDO) and subgroup in panel C of Table 1. In some analyses, we also consider changes from the beginning to the end of a calendar year.

For background information, Internet Appendix Figure A.4 shows the evolution of defaults through time for CLO, ABS, MBS, and CDOs, with defaults increasing in that order. The ABS deals have 45% of capital in default as of December 2010, and CDOs experience a 74% default rate.[17]

3. Do Reputable Underwriters Issue Better Securities?

We now examine the relation between underwriter reputation and deal performance.

3.1 Reputation and performance

Figure 4 plots relative default performance for high- and low-reputation underwriters for CLO, MBS, ABS, and CDOs separately. None of the results support the classical view that high-reputation underwriters issued better performing securities. Within CLOs, there is considerably less default and little difference between reputation groups. In contrast, in the MBS, ABS, and CDO

[15] In additional analyses reported in the Internet Appendix, we use a secondary measure of performance based on the deal rating, which is constructed by calculating a value-weighted average rating score of all the tranches that belong to each particular deal. We compute the difference between the rating deal as of December 2010 and the rating deal at issuance. This measure has the advantage of being continuous and capturing minor events that may not lead to default and the disadvantage of depending on the initial rating of the securities at issuance.

[16] Often, rating agencies interrupt the rating service by effectively withdrawing the rating. This might happen for two reasons: the security might be in default and the deal manager thus stopped paying the rating fee, or the deal is fully repaid. If the final balance of the security (which is also available through Bloomberg) reports both a positive outstanding value and losses, and all ratings are withdrawn, then we consider the security to be in default. If the balance is zero and there are no reported losses, we consider the security to be repaid in full with a rating equal to the last known rating.

[17] Cordell, Huang, and Williams (2011) estimate that 65% of the CDO principal was lost with 70% of these losses having occurred as of March 2011. Because our numbers are for default and do not include recovery, they are comparable to a sample of 727 structured finance ABS CDOs analyzed by Cordell, Huang, and Williams (2011).

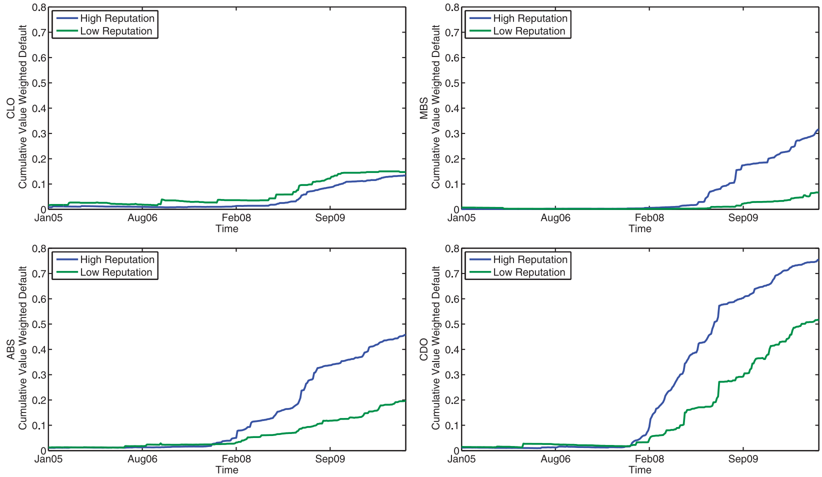


Figure 4
Cumulative percentage of deal in default by reputation type
This figure shows the cumulative proportion of tranches in default for securities issued from January 2000 through December of 2010. We report results for CLO, MBS, ABS and CDO separately. For each market, (e.g., ABS) we report the results for two different underwriter reputation groups. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The reputation score is obtained from Professor Jay Ritter's Web site. The score is a measure of the prestige ranking of IPO underwriters obtained following the method proposed by Carter and Manaster (1990): it is on a 0 to 9 scale, and is based on the pecking order seen in "tombstone" advertisements. Underwriters with a score greater than or equal to eight are deemed "High Reputation;" underwriters with a score lower than eight are deemed "Low Reputation." For deals that have more than one underwriter, the reputation score is calculated as the maximum score across underwriters. A detailed list of the average score and the issuance volume at the bank level is available in Appendix Table A.2. The data are from Bloomberg.

markets, high-reputation underwriters have higher levels of default than low-reputation underwriters. We now turn to regression analysis to examine these relationships more rigorously.

In panel A of Table 2 the dependent variable is the proportion of the deal in default (i.e., value-weighted proportion of tranches in default relative to the total size of the deal) as of December 2010 for all deals issued from January 1, 2000 to December 31, 2010. The main variable of interest is an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score greater than or equal to eight. The regression models reported in Columns 1 and 2 are without any controls. From an investor standpoint, the regression asks how investors fared if they bought structured products without knowing anything else about the security other than the reputation of the underwriter. Interestingly, high-reputation underwriters issued securitized products that subsequently ended up with an economically large 15.5% more capital in default.

Next, through vintage-by-collateral-type controls, we are examining relative performance of high- versus low- reputation underwriters within each part of the market. In Column 2, we include vintage-by-collateral-type fixed effects, so

Table 2
Impact of high reputation on proportion of deal in default

Panel A: Overall

	January 2000 to December 2010					
	(1)	(2)	(3)	(4)	(5)	(6)
High reputation	0.155	0.076	0.081	0.074	0.069	0.078
	(4.44)	(4.83)	(4.92)	(4.57)	(4.40)	(4.43)
US deal			0.165	0.164	0.155	0.154
			(4.22)	(4.22)	(4.19)	(4.19)
Amount			−0.008	−0.008	−0.011	−0.010
			(−1.19)	(−1.18)	(−1.77)	(−1.53)
Maturity			0.061	0.061	0.059	0.055
			(3.68)	(3.66)	(3.51)	(3.01)
Initial rating			0.012	0.012	0.014	0.015
			(2.32)	(2.34)	(3.01)	(3.11)
AAA fraction			−0.033	−0.033	−0.023	−0.015
			(−1.00)	(−0.99)	(−0.70)	(−0.46)
Synthetic			0.163	0.162	0.162	0.173
			(3.39)	(3.36)	(3.38)	(3.51)
Investment bank				0.014	0.015	0.014
				(1.70)	(1.83)	(2.00)
Bank size						−0.003
						(−0.45)
Bank book-to-market						−0.003
						(−0.58)
Constant	0.163	−0.076	−0.168	−0.170	−0.038	−0.037
	(7.50)	(−4.83)	(−1.15)	(−1.16)	(−0.27)	(−0.22)
Credit enhancement control					x	x
Vintage by type fixed effects		x	x	x	x	x
Adjusted R^2	0.006	0.450	0.483	0.483	0.486	0.497
Observations	11,619	11,619	11,615	11,615	11,615	10,861

that each collateral type is divided into semester issuance groups. To focus on the detailed types of collateral and not on the broad categories, collateral types are defined as the classes within each group as shown in Table 1. For example, the fixed effects for ABS control for the specific type of collateral issued (auto, credit card, equipment, nonprime housing, etc.) each semester. The regression specification cuts the magnitude of the coefficient compared with no controls, but high-reputation underwriters still experience an economically large 7.6% more capital in default.

We then include additional controls to see if the performance differences can be explained by other characteristics of the deal. The additional control variables are: an indicator variable that is equal to one when the deal is denominated in USD (USD Deal), the natural logarithm of the dollar size of the deal (Amount), the log of the years from issuance to the stated maturity

Panel B: Performance by year

	2001 (1)	2002 (2)	2003 (3)	2004 (4)	2005 (5)	2006 (6)	2007 (7)	2008 (8)	2009 (9)	2010 (10)
High reputation	0.001	0.010	0.002	0.000	0.004	0.001	0.010	0.046	0.008	−0.002
	(1.00)	(1.97)	(0.88)	(0.07)	(1.33)	(0.23)	(2.38)	(3.70)	(0.70)	(−0.54)
US deal	−0.000	0.013	0.003	−0.000	0.000	0.003	0.000	0.039	0.076	0.000
	(−0.40)	(1.58)	(1.18)	(−0.24)	(0.02)	(2.10)	(0.04)	(3.85)	(3.05)	(0.42)
Amount	0.000	−0.003	0.001	−0.001	0.001	−0.003	0.002	−0.006	−0.016	−0.001
	(0.77)	(−0.93)	(1.23)	(−0.81)	(1.00)	(−0.97)	(2.01)	(−2.47)	(−2.95)	(−1.33)
Maturity	0.000	−0.018	−0.005	0.002	−0.001	0.002	0.004	0.055	0.002	0.001
	(0.89)	(−1.36)	(−1.60)	(1.49)	(−0.52)	(0.81)	(1.63)	(3.34)	(0.14)	(1.75)
Initial rating	0.000	−0.001	0.000	−0.000	−0.001	0.001	0.002	0.004	−0.004	0.000
	(0.74)	(−0.54)	(0.93)	(−0.09)	(−1.11)	(0.69)	(1.61)	(0.89)	(−0.84)	(0.36)
AAA fraction	0.000	0.008	−0.002	−0.004	−0.010	0.001	−0.008	−0.029	−0.068	0.002
	(0.76)	(0.49)	(−0.54)	(−0.82)	(−0.89)	(0.27)	(−0.91)	(−1.28)	(−2.28)	(1.58)
Synthetic	0.000	0.006	−0.003	0.005	−0.004	−0.009	0.010	0.134	0.010	0.003
	(0.95)	(1.23)	(−1.23)	(0.90)	(−1.34)	(−1.73)	(0.66)	(4.15)	(0.34)	(0.91)
Investment bank	−0.000	0.003	0.001	−0.000	−0.003	0.002	−0.001	0.009	0.014	0.001
	(−0.88)	(1.22)	(0.63)	(−0.06)	(−1.25)	(0.77)	(−0.30)	(1.54)	(2.52)	(1.49)
Bank size	0.000	0.001	−0.000	0.001	−0.001	0.002	−0.008	−0.000	0.002	0.000
	(0.88)	(0.64)	(−0.22)	(0.84)	(−0.38)	(1.06)	(−2.32)	(−0.06)	(0.28)	(0.45)
Bank book-to-market	0.001	−0.015	0.000	−0.003	0.000	0.004	−0.018	−0.023	0.007	−0.000
	(0.80)	(−1.04)	(0.04)	(−0.71)	(0.12)	(0.89)	(−1.47)	(−1.63)	(0.48)	(−0.91)
Credit enhancement	x	x	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x	x	x
Adjusted R^2	0.068	0.021	0.288	0.325	0.039	0.036	0.038	0.364	0.245	0.007
Observations	315	760	1,435	2,612	4,183	6,065	8,259	10,151	10,470	10,640

(Maturity), the deal's initial rating (Initial Rating), the proportion of AAA-rated tranches AAA (AAA Fraction), and whether Bloomberg indicates that the deal is (also) supported by some synthetic asset in the form of a short position in a CDS contract written over another ABS, MBS or CLO security (Synthetic). The results with controls (Column 3) are similar to those reported in Column 2. The positive relation between synthetic assets and default is consistent with the evidence of Ghent, Torous, and Valkanov (2013) and Furfine (2014) that more complex MBSs underperform.

It is possible that independence from regulatory bodies might play a role in how banks construct securities. The underwriting unit of a commercial bank could have less freedom to produce securities that might jeopardize the reputation of the entire bank. To control for this possibility we introduce, in Column 4, an indicator variable that is set equal to one when underwriters are classified as an investment bank, according to the Bloomberg industry classification. We find that investment banks have a higher percentage of default rates (approximately 1.4%), but this effect does not subsume the impact of reputation.

Panel C: Performance by vintage

	2000 (1)	2001 (2)	2002 (3)	2003 (4)	2004 (5)	2005 (6)	2006 (7)	2007 (8)	2008 (9)	2009 (10)	2010 (11)
High reputation	−0. 013	0. 146	0. 038	0. 113	0. 077	0. 080	0. 142	0. 096	0. 083	0. 055	−0. 011
	(−0. 16)	(2. 92)	(1. 12)	(4. 06)	(1. 88)	(2. 43)	(2. 70)	(1. 74)	(1. 79)	(0. 83)	(−1. 13)
US deal	0. 050	0. 048	0. 021	0. 004	0. 108	0. 177	0. 277	0. 262	0. 026	−0. 096	−0. 001
	(0. 50)	(1. 18)	(0. 51)	(0. 11)	(2. 21)	(4. 26)	(2. 59)	(3. 14)	(1. 17)	(−1. 31)	(−0. 65)
Amount	0. 034	−0. 017	0. 026	0. 010	0. 007	0. 002	−0. 005	−0. 044	−0. 018	0. 007	0. 000
	(1. 93)	(−1. 39)	(1. 13)	(0. 52)	(0. 56)	(0. 18)	(−0. 37)	(−3. 03)	(−1. 10)	(0. 54)	(0. 73)
Maturity	0. 072	−0. 001	0. 025	0. 045	0. 100	−0. 056	0. 080	0. 086	−0. 010	−0. 072	0. 002
	(1. 34)	(−0. 03)	(0. 95)	(2. 51)	(2. 16)	(−1. 39)	(3. 17)	(2. 24)	(−0. 17)	(−1. 00)	(0. 87)
Initial rating	0. 026	−0. 010	0. 019	0. 003	0. 023	0. 007	0. 017	0. 020	0. 021	0. 007	0. 002
	(1. 23)	(−1. 00)	(1. 25)	(0. 34)	(1. 71)	(0. 69)	(1. 37)	(2. 22)	(1. 49)	(0. 27)	(1. 21)
AAA fraction	0. 218	−0. 050	0. 085	−0. 027	0. 004	−0. 176	−0. 102	0. 062	0. 086	−0. 243	0. 006
	(1. 78)	(−1. 13)	(0. 87)	(−0. 51)	(0. 05)	(−2. 28)	(−1. 21)	(0. 89)	(1. 02)	(−2. 07)	(1. 57)
Synthetic	0. 030	0. 451	0. 006	0. 077	−0. 007	0. 085	0. 157	0. 253	−0. 125		
	(0. 14)	(1. 04)	(0. 09)	(1. 45)	(−0. 07)	(1. 11)	(1. 86)	(3. 48)	(−1. 90)		
Investment bank	−0. 045	−0. 010	0. 014	−0. 000	−0. 017	0. 028	0. 019	0. 030	−0. 012	−0. 024	0. 000
	(−0. 72)	(−0. 28)	(0. 54)	(−0. 01)	(−1. 14)	(1. 57)	(1. 28)	(1. 66)	(−0. 64)	(−0. 59)	(0. 68)
Bank size	−0. 021	−0. 011	0. 064	−0. 001	−0. 026	−0. 028	−0. 014	0. 013	−0. 010	0. 014	0. 001
	(−0. 30)	(−0. 43)	(2. 15)	(−0. 09)	(−1. 80)	(−2. 32)	(−1. 27)	(0. 40)	(−0. 30)	(0. 32)	(0. 90)
Bank book-to-market	−0. 066	−0. 038	−0. 070	0. 019	−0. 064	−0. 095	0. 016	0. 039	0. 029	0. 005	−0. 001
	(−0. 57)	(−0. 46)	(−1. 38)	(0. 55)	(−0. 92)	(−2. 04)	(0. 24)	(0. 81)	(0. 70)	(0. 71)	(−0. 83)
Credit enhancement control	x	x	x	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x	x	x	x
Adjusted R^2	0. 234	0. 209	0. 185	0. 222	0. 296	0. 352	0. 459	0. 503	0. 320	0. 111	−0. 050
Observations	314	446	678	1,178	1,569	1,895	2,206	1,894	304	169	208

Panel D: CLO, MBS, ABS, and CDO, January 2000 to December 2010

	CLO		MBS		ABS		CDO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High reputation	−0.020	−0.036	0.094	0.086	0.070	0.070	0.134	0.138
	(−0.79)	(−1.00)	(2.80)	(2.52)	(2.84)	(2.66)	(3.35)	(3.21)
US deal	−0.003	0.010	0.267	0.255	0.064	0.042	0.316	0.322
	(−0.18)	(0.57)	(4.04)	(4.05)	(3.04)	(2.56)	(4.91)	(5.20)
Amount	−0.023	−0.029	0.001	−0.001	−0.012	−0.010	−0.005	−0.005
	(−1.27)	(−1.63)	(0.09)	(−0.06)	(−0.97)	(−0.81)	(−0.44)	(−0.38)
Maturity	0.046	0.067	−0.045	−0.043	0.029	0.012	0.181	0.180
	(1.61)	(2.18)	(−1.94)	(−1.89)	(1.81)	(0.73)	(8.46)	(8.94)
Initial rating	0.051	0.046	0.040	0.041	0.003	0.003	0.014	0.012
	(2.31)	(2.38)	(4.53)	(4.82)	(0.40)	(0.41)	(1.33)	(1.19)
AAA fraction	−0.075	−0.068	0.066	0.082	−0.074	−0.066	0.014	0.008
	(−0.84)	(−0.76)	(0.67)	(0.85)	(−1.59)	(−1.34)	(0.25)	(0.15)
Synthetic	0.050	0.062					0.142	0.153
	(0.65)	(0.83)					(3.69)	(3.97)
Investment bank	−0.005	−0.000	0.023	0.014	0.027	0.035	−0.013	−0.015
	(−0.32)	(−0.00)	(2.09)	(1.21)	(1.89)	(3.47)	(−0.48)	(−0.58)
Bank size		−0.005		−0.021		0.008		0.023
		(−0.35)		(−2.08)		(0.84)		(0.78)
Bank book-to-market		0.007		0.005		−0.006		−0.093
		(0.14)		(0.38)		(−1.53)		(−1.54)
Credit enhancement control	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x
Adjusted R^2	0.478	0.533	0.459	0.467	0.451	0.460	0.490	0.504
Observations	1,055	999	3,563	3,402	5,500	5,029	1,124	1,090

This table reports estimation results of regression models in which the dependent variable is the proportion of deal that is rated in default relative. The main variable of interest is an indicator variable (High Reputation) set equal to one for deals with an underwriter reputation score larger or equal to eight. The variable is constructed based on reputation scores obtained from Professor Jay Ritter's Web site. The score is a measure of the prestige ranking of IPO underwriters obtained following the method proposed by Carter and Manaster (1990): it is on a 0 to 9 scale and is based on the pecking order seen in "tombstone" advertisements. We match Ritter's dataset to our dataset by name of the underwriter institution. For deals that have more than one underwriter, the reputation score is calculated as the maximum score across underwriters. Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Panel A presents results for the full sample, and the dependent variable is the proportion of deal in default as of December 2010. In panel B the dependent variable is the difference in the percentage of deal in default for a deal between the end and the beginning of each year, starting in 2000 throughout 2010. Panel C reports results of regressions similar to that reported in panel A but disaggregated by vintage year. For example, the first column reports results of the percentage of deal in default in December 2010 for securities issued between January 1, 2000 and December 31, 2000. Panel D presents results of regressions for disaggregated markets of CLO, MBS, ABS, and CDO, respectively, where the dependent variable is the percentage of deal in default as of December 2010. Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing the deals, as presented in Table 1. Most regression specifications contain vintage (semester) by type fixed effects, and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but only reported in panel A. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

The presence of credit enhancements might also affect investor's perception of securities and hence influence the ability of originators to market securities with particular collateral profiles. Thus, we include in Column 5 a set of indicator variables that account for the presence of the most widely used form of credit enhancements: collateral accounts, cross-collateralization, insurance, letters of credit, overcollateralization, reserve accounts, spread accounts, and subordination. We find that their inclusions do not significantly alter the economic effect of reputation.

Finally, it is possible that our high-reputation measure is simply a proxy for bank size or the profitability of the bank. Therefore, in Column 6 we include as controls the natural logarithm of the total assets of the underwriter (Bank Size) and the book-to-market equity ratio (Bank Book-to-Market) at the quarter end closest to the security issuance. The results are similar to those reported in the previous columns.

Although the results reported in panel A of Table 2 indicate that our predictions might be accurate, a more direct test of our model can be done by comparing securities' performance across different years. Our model predicts that a difference in performance should be observable only during periods in which the underlying market experiences a downturn (i.e., the bad state of nature is realized). Our sample period is characterized by booming years in the credit market and by the recent financial crisis. Interestingly, by analyzing news reports, we find that in 2002 the manufactured housing market experienced a crisis and many tranches of ABS experienced heavy losses and downgrading (Yoon 2004). In panel B of Table 2, we consider the changes in performance on a yearly basis by measuring the percentage change in the proportion of assets in default from the beginning to the end of each calendar year.[18] High-reputation underwriters underperformed in 2002, 2007, and 2008. We find no statistically significant difference in performance in the other years. Also, it is interesting to observe that there are no years in which securities from high-reputation underwriters outperform, as the traditional view predicts. We note that there might only be enough power to disentangle performance differences between high- and low-reputation underwriters during crisis periods, when a significant number of defaults and downgrades occur. Nevertheless, it is interesting that the underperformance of high-reputation underwriters is present in the three years mentioned and that these years are consistent with the intuition from our model that the difference in performance of securities does not appear until the bad state occurs.

If the performance of high-reputation underwriters is due to mistakes in a few deals, one would expect them to issue better securities in some years and worse securities in others. In other words, we would expect to find some variation in the relationship between performance and reputation across

[18] We start tracking the performance of assets issued during the year at the beginning of the next year.

different years of issuance. In panel C, we consider the proportion of the deal in default as of December 2010 but separately analyze securities issued in different cohorts. We define a cohort as the pool of securities issued in any particular calendar year. Interestingly, panel C shows that in no vintage year over the 2000 to 2010 period did high-reputation underwriters issue securities with statistically significant higher performance than securities issued by low-reputation underwriters. Instead, securities issued by high-reputation underwriters in 2001 and from 2003 to 2008 had a larger percentage of future defaults.

Finally, in panel D of Table 2, we examine the relationship between reputation and proportion of the deal in default as of December 2010 (i.e., similarly to panel A) within each market. For CLOs, there is an insignificant relationship between underwriter reputation and future defaults. Both with and without bank-level controls, high-reputation underwriters underperform in the ABS, MBS, and CDO markets; their deals subsequently experience between 7% and 14% of capital in default. The results in panel D suggest that the failure of reputable underwriters to provide value for their clients is not limited to one area of structured finance and is not simply caused by poor choices about which general types of securities to produce. It rests instead on the specific securities they produced within each of these three important structured finance spaces.

We also examine rating changes (downgrades) on a deal basis from issuance through December 2010 (results are reported in Table A.3 of the Internet Appendix). When controlling for security characteristics and bank characteristics, high-reputation underwriters issue securities that underperform those from low-reputation underwriters by about one rating notch. Results mirroring other panels of Table 2 but with rating changes as the dependent variable are also examined. Overall, the results with both default and downgrades indicate that high-reputation underwriters issued structured products that underperformed those issued by low-reputation underwriters.

3.2 Alternative explanations

In this section, we investigate alternative explanations for our findings, which relate to the reputation measure, security complexity, asset quality, and particular banks driving the results.

3.2.1 Reputation measure. Because we use a measure of reputation from the equity market, a natural question is whether our results are robust to an alternative measure from the fixed income market. In our regression specification, we substitute the reputation variable constructed using IPO tombstones with the variables constructed from the fixed income league ranking tables (i.e., Top 10 League Rank and League Table Rank) and report the results in Table 3. We find a positive relation between these alternative measures of reputation at origination of the deal and the proportion of the deal in default as of December 2010. With our full set of controls, banks belonging to the top ten

Table 3
Alternative measures

	(1)	(2)	(3)	(4)	(5)	(6)
Top 10 league rank	0.043	0.024	0.037			
	(4.97)	(3.61)	(4.65)			
League rank				0.009	0.005	0.003
				(3.93)	(2.45)	(1.70)
US deal		0.149	0.147		0.150	0.148
		(3.81)	(4.07)		(3.86)	(4.07)
Amount		−0.011	−0.006		−0.011	−0.006
		(−1.71)	(−1.05)		(−1.69)	(−1.02)
Maturity		0.059	0.062		0.058	0.060
		(4.22)	(3.40)		(4.21)	(3.34)
Initial rating		0.010	0.015		0.010	0.015
		(1.87)	(2.70)		(1.91)	(2.71)
AAA fraction		−0.054	−0.035		−0.052	−0.033
		(−1.76)	(−0.98)		(−1.68)	(−0.93)
Synthetic		0.180	0.177		0.179	0.176
		(4.26)	(3.76)		(4.26)	(3.77)
Investment bank		0.008	0.013		0.011	0.017
		(1.11)	(1.69)		(1.50)	(2.00)
Bank size			−0.013			−0.008
			(−1.42)			(−0.81)
Bank book−to−market			−0.006			−0.006
			(−1.03)			(−1.07)
Credit enhancement control		x	x		x	x
Vintage by type fixed effects	x	x	x	x	x	x
Adjusted R^2	0.420	0.459	0.487	0.419	0.459	0.486
Observations	14,474	14,470	11,395	14,474	14,470	11,395

This table reports estimation results of regression models in which the dependent variable is the proportion of the deal that is rated in default as of December 2010. The main variables of interest are an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank) in Columns 1, 2, and 3, and the negative of the natural logarithm of the deal's underwriter position in the league rank table of fixed income desks (League Rank) Columns 4, 5, and 6. Both variables are measured as of the issuance date of the security they are paired with. For deals that have more than one underwriter, we consider the rank of the highest placed underwriter. Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing up the deals, as presented in Table 1. Most regression specifications contain vintage (semester) by type fixed effects and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

of the league tables have 3.7% more capital in default than banks ranked lower than ten. Overall, the evidence does not support the conventional wisdom that reputable underwriters issue better securities.

An additional concern with the IPO reputation measure is that the great majority of the securities are classified as originating by the high-reputation group. We address this problem in three ways. First, as described in the previous section, we also consider the underwriter's rank in the league table. The total volume of securities originated by underwriters in the top ten of the league table accounts for 51% of the deals, thus providing a more even split of the sample. As shown in Table 3, we still obtain a significant and economically important difference in performance.

Second, we address the problem in the context of our main measure of reputation by adopting a bootstrap matching procedure that is designed to balance the sample composition.[19] Results are displayed in Figure 5, where we compare the sample mean percentage of deal in default for the actual group of low-reputation deals to the bootstrap distribution of matched deals with high reputation. The null hypothesis that the sample mean proportion of deal in default for the low-reputation group is drawn from the bootstrap distribution of the sample mean of matched high-reputation deals is rejected at any conventional significance level.

Third, we repeat our regressions for which the dependent variable is the percentage of the deal in default as of December 2010 but disaggregate the reputation variables into finer groups. We consider four categories for the IPO reputation: score equal to 9, score equal to 8, score equal to 7, and those below seven. We also evaluate four categories for the league table measure: rank between 1 and 10, rank between 11 and 25, rank between 26 and 200, and those beyond 200.[20] We estimate the first three and let the constant absorb the effect of the remaining group.

Aside from disentangling the magnitude of the effect of reputation on performance for various "levels" of reputation, this analysis also allows us to potentially detect any nonmonotonicity in the relationship. Results are reported in Internet Appendix Table A.6. Based on the IPO measure, there is no detectable difference between a reputation of 8 and 9. This may reflect the relatively flat relationship between the commitment probability and the probability of producing time bombs, as shown in Figure 1, panel B. As such, this provides some evidence in favor of an interpretation of our results in which reputation is "undeserved" in the sense that the true commitment probability does not match the prior on the commitment probability. In this case, a marginally

[19] We randomly assign each low-reputation deal to a high-reputation deal with the same characteristics: collateral type, issue amount, calendar quarter of issuance, issuance rating (within one notch), proportion of tranches in default (within 10%), synthetic composition of the collateral, type of bank (investment versus commercial), and credit enhancements. We repeat the random assignment 5,000 times with replacement.

[20] The break points for the grouping are chosen so that all the groups other than the first one have approximately the same amount of capital issued.

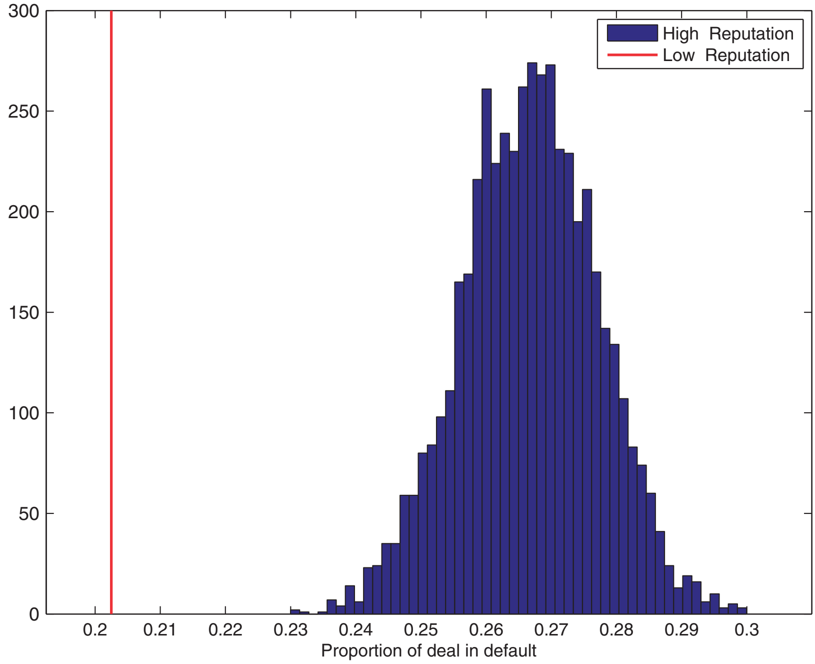


Figure 5
Bootstrap distribution of proportions of deal in default
This figure shows a comparison of the sample mean proportion of deal in default for low-reputation deals (vertical line) to the bootstrap distribution of matched high- reputation deals. We randomly assign each low-reputation deal to a high-reputation deal with the same characteristics: collateral type, issue amount, calendar quarter of issuance, issuance rating (within one notch), proportion of tranches in default (within 10%), synthetic composition of the collateral, type of bank (investment versus commercial), and credit enhancements. We repeat the random assignment 5,000 times with replacement. The reputation score is obtained from Professor Jay Ritter's website. The score is a measure of the prestige ranking of IPO underwriters obtained following the method proposed by Carter and Manaster (1990): it is on a 0 to 9 scale, and is based on the pecking order seen in "tombstone" advertisements. Underwriters with a score greater than or equal to eight are deemed "High Reputation;" underwriters with a score lower than eight are deemed "Low Reputation." For deals that have more than one underwriter, the reputation score is calculated as the maximum score across underwriters. A detailed list of the average score and the issuance volume at the bank level is available in Appendix Table A.2. The sample is from January 2000 through December 2010, and the data are from Bloomberg.

higher reputation does not appreciably change the quality of the securities produced by strategic players, and the absence of a direct effect of including more commitment types leads to a flat relationship between security payoff and commitment probability. When using the league table measure, however, we detect a more linear relationship between reputation and performance.

3.2.2 Complexity, asset quality, housing, and AAA securities. We first consider whether there might be an omitted variables problem associated with complexity. If high reputation is correlated with skill, perhaps only the high-reputation underwriters have the ability to produce the most complex deals within each space. Then the most complicated deals turned out to be those that were most sensitive to an economic downturn.

Our main analysis addresses this possibility through the use of fixed effects by type, by vintage, and through control variables, such as the Synthetic dummy variable. Nevertheless, as a robustness check we exclude all deals for which the collateral pool includes some synthetic asset in the form of a short position on a CDS contract written on ABS and MBS securities and re-estimate our regressions in which the dependent variable is the proportion of the deal in default as of December 2010 and the main dependent variable is either the IPO high reputation (High Reputation) or the league table high reputation (Top 10 League Rank). We report results in Columns 1 and 2 of Table 4. In this way we eliminate deals that we can identify as the most complex and check whether the relation between performance and reputation exists even among deals that are not supported by any derivative position. Deals from high-reputation underwriters end up with a highly significant 8.4% more capital in default (4.4% for Top 10 League Rank underwriters).

A second possibility is that the difference in performance was just a function of high-reputation underwriters using different types of collateral. In the CDO and CLO space we have data regarding the underlying quality of the loan and can include controls as to whether the collateral is high grade or mezzanine. Estimating our specifications, where the dependent variable is the proportion of capital in default as of December 2010, for a subset of deals with these detailed data (Columns 3 and 4, Table 4) yields similar inferences, indicating that underwriter performance is not driven by basic underlying loan quality. We address this particular point further in Section 3.3.2, where we consider a sample of RMBS for which we have detailed information about the collateral composition.

A third question is whether the poor performance of reputable underwriters is purely concentrated in housing collateral. Maybe the reputable banks specialized in securitizing housing collateral that was of a riskier nature. Because housing collateral is spread throughout MBS, ABS, and CDOs, our results could reflect that reputable banks were more active in issuing poorly performing housing-related securities and that this tendency is not adequately captured by our fixed effects and controls. To evaluate this possible explanation we narrow our focus to non-housing-related securities. Within ABS, we focus on auto loans, credit cards, equipment, and student loans, and within MBS we only include CMBS.[21] In Columns 5 and 6, Table 4 we find a positive relationship between our measures of high reputation and the proportion of the deal in default as of December 2010.

Fourth, there may be a concern that our results are driven by lower tier tranches of deals, while the main focus of structured finance is to create AAA

21 Results are similar if we exclude CMBS from this analysis.

Table 4
Reputation and asset quality

	Overall No synthetics (1)	(2)	CDO+CLO quality (3)	(4)	ABS+CMBS no housing (5)	(6)	Overall AAA tranches (7)	(8)
High reputation	0.084		0.075		0.051		0.063	
	(4.56)		(2.68)		(3.72)		(3.39)	
Top 10 league rank		0.044		0.017		0.022		0.029
		(5.69)		(0.83)		(2.60)		(3.67)
US deal	0.149	0.140	0.132	0.116	0.050	0.045	0.164	0.154
	(3.83)	(3.74)	(4.02)	(4.44)	(2.54)	(2.36)	(4.15)	(4.11)
Amount	−0.008	−0.008	−0.014	−0.011	−0.030	−0.031	−0.013	−0.009
	(−1.16)	(−1.27)	(−1.56)	(−0.85)	(−3.10)	(−3.17)	(−1.54)	(−1.14)
Maturity	0.031	0.041	0.155	0.157	0.026	0.028	0.042	0.050
	(2.21)	(2.71)	(6.78)	(6.91)	(2.11)	(2.03)	(1.86)	(2.08)
Initial rating	0.016	0.012	0.017	0.014	0.012	0.013	−0.005	−0.008
	(3.10)	(1.99)	(1.84)	(1.67)	(1.62)	(1.68)	(−0.43)	(−0.69)
AAA fraction	−0.019	−0.044	−0.036	−0.058	0.036	0.043	0.008	−0.009
	(−0.53)	(−1.18)	(−0.82)	(−1.49)	(0.79)	(0.88)	(0.14)	(−0.15)
Synthetic			0.154	0.153			0.215	0.212
			(4.33)	(4.03)			(3.92)	(3.90)
Low quality			0.110	0.101				
			(5.42)	(4.54)				
Investment bank	0.016	0.024	−0.001	0.003	0.008	0.017	0.009	0.002
	(2.33)	(2.83)	(−0.05)	(0.16)	(0.88)	(1.67)	(1.35)	(0.29)
Bank size	−0.007	−0.020	0.001	0.002	−0.004	−0.003	−0.001	−0.016
	(−1.06)	(−2.13)	(0.07)	(0.19)	(−0.47)	(−0.43)	(−0.07)	(−1.68)
Bank book-to-market	−0.003	−0.002	−0.022	−0.015	−0.002	−0.001	−0.009	−0.008
	(−0.53)	(−0.45)	(−0.59)	(−0.42)	(−1.13)	(−0.61)	(−2.46)	(−2.04)
Credit enhancement control	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x
Adjusted R^2	0.479	0.474	0.653	0.651	0.188	0.193	0.528	0.518
Observations	10,436	10,604	2,135	2,141	1,921	1,821	9,058	9,233

This table reports estimation results of regression models in which the dependent variable is the proportion of the deal that is rated in default as of December 2010. In Columns 1 and 2, we report results in which the dependent variables are based only on the tranches that were rated AAA at issuance. In Columns 3 and 4, we report results obtained excluding deals that are synthetics (i.e., the collateral pool contains some short position in credit default swaps); in Columns 5 and 6, we only consider nonhousing ABS and CMBS deals. In Columns 7 and 8, we report results for CLO and CDO deals for which we have information about the quality of the collateral assets. The main variable of interest is either an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score larger or equal to eight, or an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank). Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing the deals, as presented in Table 1. All regression specifications contain vintage (semester) by type fixed effects and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

tranches. Perhaps, then, the focus should be only on these highly rated tranches. These are also likely to be the tranches that are bought by investors who are most reliant upon ratings and the reputation of the underwriter, rather than on their own analysis. In the final two specifications, Columns 7 and 8 of Table 4, we estimate our regressions, where the dependent variable is the proportion of the deal in default as of December 2010 and include only the performance of tranches rated AAA at issuance. We find that high-reputation banks issue structured products in which an additional 6.3% of the collateral ends in default (2.9% for Top 10 League Rank banks), even after controlling for fixed effects and bank characteristics.

3.2.3 Lehman Brothers, Bear Sterns, and bank identity. It is well known that two large and reputable investment banks, Lehman Brothers and Bear Sterns, failed because of their exposure to structured products. Perhaps the presence of these large banks with high reputation scores in our data drives the presence of a positive relationship between reputation and proportion of deal in default as of December 2010. In Columns 1 and 2 of Table 5 we exclude these two banks from our analysis. High reputation has a similar strong and positive relationship with default.

A second related concern is that our results could be driven by one particular underwriter of low reputation that performed particularly well. To examine the sensitivity of our findings to the performance of particular banks, we take the largest five banks with low reputation and exclude them from the analysis. Results are reported in Columns 3 and 4 of Table 5. The economic and statistical significance of the findings are similar with these underwriters excluded.

Third, in an attempt to shed more light on the functional form of the relationship between reputation and performance, we remove underwriters in the tails of the reputation distribution: in particular, we remove the top five underwriters with high reputation (high rank) by volume (i.e., the ones with the most issuance) and the bottom five low reputation (low rank) by volume (i.e., the one with the least issuance). Results reported in Columns 5 and 6 of Table 5 show that our main results are not due to the most reputable and active banks and/or to the least reputable and least active banks.

A fourth possible concern is that our findings could be driven by differences in our U.S. versus non-U.S. dollar denominated securities.[22] Columns 7 and 8 of Table 5 show that the performance for only U.S. securities is quite similar to our main findings.

3.3 Why did securities from reputable underwriters underperform?

In this section we ask why the securities from high-reputation underwriters underperformed. First, we examine whether the underperformance is related to

[22] We use currency of deal denomination because country of issuance is often missing in the data.

Table 5
Reputation and bank identity

	Overall no Lehman/Bear (1)	(2)	Overall no bottom rep (3)	(4)	Overall no top−bottom (5)	(6)	Overall U.S. only (7)	(8)
High reputation	0.080		0.077		0.073		0.083	
	(4.56)		(4.42)		(3.67)		(4.03)	
Top 10 league rank		0.053		0.045		0.046		0.048
		(6.10)		(5.94)		(4.27)		(6.21)
US deal	0.139	0.135	0.154	0.152	0.143	0.142		
	(3.78)	(3.72)	(4.19)	(4.17)	(3.98)	(4.01)		
Amount	−0.018	−0.021	−0.010	−0.013	−0.018	−0.008	−0.001	−0.005
	(−2.53)	(−3.08)	(−1.54)	(−1.98)	(−2.25)	(−1.20)	(−0.14)	(−0.61)
Maturity	0.049	0.052	0.056	0.059	0.030	0.034	0.033	0.034
	(2.47)	(2.50)	(3.02)	(3.05)	(1.87)	(1.98)	(2.41)	(2.29)
Initial rating	0.014	0.007	0.015	0.009	0.014	0.011	0.018	0.012
	(2.74)	(1.19)	(3.11)	(1.81)	(2.53)	(1.86)	(3.19)	(1.99)
AAA fraction	−0.009	−0.038	−0.015	−0.040	0.005	−0.050	−0.011	−0.040
	(−0.28)	(−1.15)	(−0.45)	(−1.20)	(0.14)	(−1.39)	(−0.28)	(−1.00)
Synthetic	0.184	0.171	0.173	0.163	0.177	0.168	0.260	0.256
	(3.40)	(3.05)	(3.51)	(3.16)	(3.68)	(3.82)	(3.17)	(3.00)
Investment bank	0.030	0.047	0.014	0.029	0.020	0.013	0.018	0.030
	(3.43)	(4.78)	(1.99)	(3.56)	(1.59)	(1.17)	(2.26)	(3.54)
Bank size	−0.011	0.001	−0.003	−0.007	0.025	−0.006	−0.003	−0.007
	(−0.98)	(0.08)	(−0.47)	(−0.86)	(1.79)	(−0.37)	(−0.49)	(−0.88)
Bank book-to-market	0.001	−0.000	−0.003	−0.002	−0.008	−0.026	−0.003	−0.001
	(0.08)	(−0.07)	(−0.59)	(−0.32)	(−0.44)	(−1.18)	(−1.11)	(−0.32)
Credit enhancement control	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x
Adjusted R^2	0.501	0.505	0.497	0.500	0.529	0.499	0.500	0.502
Observations	8,687	8,047	10,859	10,219	5,306	6,455	8,389	7,810

This table reports estimation results of regression models in which the dependent variable is the proportion of the deal that is rated in default as of December 2010. In Columns 1 and 2, we report results obtained on a sample that excludes Lehman Brothers and Bear Stearns. In Columns 3 and 4, we report results obtained excluding the five largest underwriters with low reputation; in Columns 5 and 6, we eliminate the top five high-reputation underwriters by volume and the bottom five low reputation by volume; in Columns 7 and 8, we only consider USD denominated securities. The main variable of interest is either an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score larger or equal to eight, or an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank). Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing up the deals, as presented in Table 1. All regression specifications contain vintage (semester) by type fixed effects and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

risk that investors perceived at the time the securities were created. Second, we examine whether the underperformance is related to properties of the collateral pool that is supporting the deals.

3.3.1 Did investors recognize that securities from reputable underwriters were riskier? It is possible that high-reputation underwriters specialized in the production of securities with higher risk, but such risks are not captured by our extensive controls. Perhaps unobserved characteristics made certain deals riskier. We consider the market's perspective of the securities' risk, as measured by the par-yields to maturity that investors were requiring at issuance. If investors required higher yields from reputable underwriters, then it would appear that market participants were, at least to some degree, aware that structured products issued by such reputable underwriters were riskier. We calculate yield spreads over LIBOR for all securities issued with a rating of AAA for which the necessary information is available.[23] We concentrate on AAA securities because the quality of pricing data for lower tranches appears to be quite inconsistent.[24]

We report our analyses in Table 6. From Columns 1 and 2 of panel A, we note that, for the smaller sample for which we have valid yield data, there is a positive and typically insignificant relation between reputation and yield spreads. The relation is positive and insignificant in CLO and CDO. For ABS, the relation is positive and significant for the IPO reputation and negative and insignificant for the league table reputation measure. Overall, the relationship in panel A indicates little evidence that investors perceived issuances from high-reputation underwriters to be riskier.

In panel B of Table 6, we examine whether the relation between high reputation and future negative performance is due to perceived risk at issuance as reflected by market yields. Panel B shows that there still generally exists a positive relation between high reputation and proportion of tranches in default even after controlling for the investors' perception of risk implied by the yield spreads at issuance.

The evidence presented in Table 6 does not support the hypothesis that high-reputation underwriters performed poorly simply because they were assembling deals that the market knew were riskier.

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[23] A large fraction of the securities have floating rates in the form of a spread to LIBOR. For those securities we compute the yield by first finding the comparable swap rate (fix to LIBOR). We then add back the spread and subtract LIBOR. For fixed rate securities, we compute yields in the traditional way and then subtract LIBOR. We then compute a principal weighted average to determine a yield spread at the deal level.

[24] We report in Table A.9 of the Internet Appendix some analyses based on subsamples for which issuance market yields could be computed for tranches with an initial rating lower than AAA. We do not find any statistically significant relation between the underwriter reputation and issuance yields for lower- rated tranches.

Table 6
Reputation and securities risk

Panel A: Dependent variable is AAA spread

	Overall		CLO		MBS		ABS		CDO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High reputation	0.119		0.034		0.015		0.143		0.034	
	(1.34)		(0.97)		(0.03)		(2.41)		(0.82)	
Top 10 league rank		0.072		0.003		0.248		−0.033		0.013
		(1.66)		(0.14)		(2.02)		(−1.03)		(0.41)
US deal	0.269	0.278	−0.077	−0.078	1.150	1.258	0.293	0.315	0.102	0.088
	(2.77)	(2.92)	(−0.71)	(−0.73)	(0.90)	(1.08)	(2.97)	(3.17)	(1.18)	(1.04)
Amount	−0.092	−0.105	−0.076	−0.070	0.041	0.046	−0.182	−0.187	−0.113	−0.112
	(−2.84)	(−3.31)	(−3.25)	(−2.74)	(0.40)	(0.44)	(−8.63)	(−8.59)	(−6.79)	(−6.74)
Maturity	0.189	0.146	0.008	−0.046	−0.162	−0.233	0.289	0.252	0.072	0.066
	(3.96)	(3.20)	(0.19)	(−0.81)	(−0.76)	(−1.11)	(5.09)	(4.59)	(1.48)	(1.39)
Initial rating	0.015	0.025	0.024	0.003	0.323	0.337	−0.109	−0.078	0.011	0.003
	(0.44)	(0.67)	(0.74)	(0.09)	(1.44)	(1.59)	(−2.57)	(−1.78)	(0.81)	(0.21)
AAA fraction	0.004	0.099	−0.032	−0.067	1.655	1.894	−0.270	−0.190	−0.046	−0.075
	(0.03)	(0.55)	(−0.20)	(−0.41)	(1.70)	(1.98)	(−1.34)	(−0.89)	(−0.51)	(−0.74)
Synthetic	0.083	0.091	0.026	0.011					0.079	0.083
	(2.17)	(2.34)	(0.31)	(0.13)					(2.89)	(2.80)
Investment bank	−0.052	−0.012	−0.010	0.013	−0.228	−0.109	0.035	0.061	−0.013	−0.005
	(−0.82)	(−0.17)	(−0.37)	(0.53)	(−1.25)	(−0.57)	(1.18)	(1.81)	(−0.44)	(−0.20)
Bank size	−0.105	−0.035	−0.007	0.015	−0.295	−0.154	−0.029	0.001	0.036	0.036
	(−2.92)	(−1.00)	(−0.36)	(0.59)	(−3.82)	(−1.69)	(−1.03)	(0.07)	(1.02)	(1.01)
Bank book-to-market	0.022	0.035	0.078	0.055	0.221	0.210	−0.003	0.005	0.028	0.022
	(0.35)	(0.68)	(0.73)	(0.50)	(1.23)	(1.17)	(−0.09)	(0.16)	(0.41)	(0.34)
Credit enhancement	x	x	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x	x	x
Adjusted R^2	0.339	0.338	0.595	0.543	0.037	0.033	0.493	0.482	0.525	0.514
Observations	8,072	8,201	904	911	2,564	2,638	3,674	3,731	930	921

3.3.2 Did correlations and collateral quality relate to high-reputation underperformance? We now examine whether the underperformance of securities originated by high-reputation underwriters was related to properties of the collateral pool that support the deals. Our goal is to investigate the possible mechanisms that led to the underperformance. Specifically, we consider how correlations and collateral quality are related to reputation.

We focus our attention on a subsample of data for which detailed information about the collateral pool composition is available. In particular, we focus on residential MBS deals that are in our main Bloomberg dataset (i.e., ABS Home Equity (subprime) plus residential MBS) and that are covered by ABSnet.[25]

ABSnet data provide access to loan-level data that give a finer classification of the quality of the mortgages and allow us to construct measures of collateral correlation/concentration. We follow Nadauld, Sherlund, and Vorkink (2011)

[25] ABSNet data includes most of the universe of nonagency loans securitized from 2002 through 2008. We thank Gonzalo Maturana for constructing and sharing the relevant variables.

Panel B: Dependent variable is proportion of deal in default

	Overall		CLO		MBS		ABS		CDO	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High reputation	0.073		−0.036		0.072		0.048		0.165	
	(4.08)		(−1.17)		(2.85)		(1.81)		(3.65)	
Top 10 league rank		0.037		−0.008		0.035		0.054		0.038
		(4.89)		(−0.56)		(3.45)		(4.47)		(1.21)
US deal	0.100	0.089	0.015	0.009	0.099	0.096	0.034	0.035	0.362	0.332
	(4.01)	(3.70)	(0.80)	(0.53)	(2.77)	(3.02)	(1.67)	(1.51)	(5.66)	(5.65)
Amount	−0.002	−0.000	−0.016	−0.013	−0.010	−0.003	−0.003	−0.003	0.010	0.013
	(−0.20)	(−0.01)	(−0.90)	(−0.74)	(−1.14)	(−0.27)	(−0.23)	(−0.22)	(0.47)	(0.74)
Maturity	0.073	0.078	0.053	0.062	0.051	0.039	0.004	0.003	0.182	0.191
	(2.98)	(3.03)	(1.76)	(1.92)	(2.62)	(1.84)	(0.18)	(0.12)	(6.91)	(7.56)
Initial rating	0.020	0.017	0.028	0.012	0.077	0.074	0.016	0.009	−0.010	−0.018
	(1.60)	(1.24)	(1.62)	(0.65)	(3.56)	(3.89)	(0.51)	(0.29)	(−0.52)	(−0.85)
AAA fraction	−0.105	−0.140	−0.029	−0.096	−0.067	−0.081	−0.175	−0.226	−0.105	−0.165
	(−1.84)	(−2.33)	(−0.27)	(−0.96)	(−0.56)	(−0.73)	(−1.53)	(−1.91)	(−1.19)	(−1.76)
Synthetic	0.168	0.166	0.116	0.143					0.160	0.155
	(3.75)	(3.72)	(1.77)	(2.19)					(4.49)	(4.25)
AAA spread	−0.001	−0.001	0.027	0.026	−0.000	−0.000	−0.015	−0.014	0.010	0.010
	(−0.89)	(−0.90)	(1.44)	(1.18)	(−0.29)	(−0.17)	(−1.40)	(−1.25)	(0.32)	(0.33)
Investment bank	0.013	0.012	0.007	−0.000	0.012	0.003	0.029	0.024	−0.008	0.020
	(1.59)	(1.52)	(0.42)	(−0.02)	(0.96)	(0.32)	(2.09)	(1.87)	(−0.24)	(0.70)
Bank size	0.010	−0.003	−0.006	−0.012	−0.023	−0.031	0.037	0.017	0.015	0.019
	(1.18)	(−0.31)	(−0.51)	(−1.05)	(−2.88)	(−2.90)	(3.54)	(1.74)	(0.52)	(0.66)
Bank book-to-market	−0.007	−0.007	0.002	0.014	−0.004	0.005	−0.006	−0.007	−0.124	−0.127
	(−1.94)	(−1.77)	(0.07)	(0.45)	(−0.51)	(0.73)	(−1.19)	(−1.31)	(−1.71)	(−2.07)
Credit enhancement	x	x	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x	x	x
Adjusted R^2	0.556	0.551	0.506	0.516	0.579	0.592	0.453	0.436	0.523	0.531
Observations	8,065	8,194	904	911	2,564	2,638	3,667	3,724	930	921

This table reports estimation results of regression models in which the dependent variables are the average spread of AAA tranches at issuance (panel A), and the proportion of the deal in default (panel B). The main variable of interest is either an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score larger or equal to eight, or an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank). Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing up the deals, as presented in Table 1. All regression specifications contain vintage (semester) by type fixed effects and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

Table 7
RMBS subsample

Panel A: Geographical concentration and reputation

	Concentration		% California		% Florida	
	(1)	(2)	(3)	(4)	(5)	(6)
High reputation	0.017		0.059		0.009	
	(0.84)		(1.93)		(1.21)	
Top 10 league rank		0.014		0.024		−0.004
		(2.84)		(3.07)		(−1.93)
Amount	0.013	0.011	0.027	0.025	0.004	0.005
	(2.64)	(2.40)	(5.25)	(4.69)	(2.32)	(3.58)
Maturity	0.076	0.076	0.090	0.085	0.006	0.009
	(2.40)	(2.58)	(2.47)	(2.49)	(0.69)	(0.94)
Initial rating	0.016	0.010	0.025	0.018	−0.002	−0.002
	(2.53)	(1.24)	(3.26)	(1.78)	(−1.11)	(−1.24)
AAA fraction	0.002	−0.043	0.073	0.026	−0.053	−0.066
	(0.05)	(−1.27)	(1.54)	(0.54)	(−4.81)	(−6.23)
Investment bank	−0.016	−0.014	−0.017	−0.014	0.003	0.004
	(−1.96)	(−2.04)	(−1.82)	(−1.69)	(1.29)	(1.70)
Bank size	−0.005	−0.013	−0.003	−0.017	−0.001	−0.003
	(−1.85)	(−3.50)	(−0.55)	(−3.32)	(−0.56)	(−1.29)
Bank book-to-market	0.011	−0.003	0.007	−0.001	0.012	0.005
	(0.66)	(−0.18)	(0.39)	(−0.07)	(2.24)	(1.13)
Credit enhancement control	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x
Adjusted R^2	0.184	0.195	0.265	0.279	0.139	0.155
Observations	3,665	3,780	3,770	3,885	3,770	3,885

and construct geographical measures of concentration for the collateral pool.[26] Specifically, a measure of collateral correlation based on the Herfindahl index (Concentration) quantifies the concentration of the states of origination of mortgages. Also in the spirit of Nadauld, Sherlund, and Vorkink (2011), we examine the percentage of loans originated in California (Percentage California) and in Florida (Percentage of Florida). The assumption here is that loans originating in the same state would be exposed to the same local shocks in the residential real estate market and would therefore have correlated payoffs.

In panel A of Table 7, we report estimation results of regression specifications in which the dependent variable is one of the measures of concentration described above, and the main dependent variable is either the IPO high reputation (High Reputation) or the league table high reputation (Top 10 League Rank). The table shows that high-reputation underwriters have no greater loan concentration on average, whereas the top ten underwriters by league table ranking do have slightly higher Herfindahl measures. There is weak evidence that both reputation measures contain a slightly higher percent of loans from California, but not from Florida.

26 Nadauld, Sherlund, and Vorkink (2011) finds that the concentration of housing collateral and loans in California varies widely across MBS deals and can explain substantial cross-sectional differences in MBS performance.

Panel B: Collateral quality and reputation

	Subprime		Alt-A		Second Lien	
	(1)	(2)	(3)	(4)	(5)	(6)
High reputation	−0.062		0.111		0.063	
	(−3.03)		(1.85)		(3.35)	
Top 10 league rank		−0.035		0.074		−0.023
		(−2.53)		(3.23)		(−3.14)
Amount	0.046	0.054	−0.012	−0.021	−0.046	−0.041
	(2.98)	(3.75)	(−0.85)	(−1.66)	(−3.95)	(−3.79)
Maturity	−0.045	−0.006	0.318	0.344	−0.045	−0.094
	(−1.42)	(−0.21)	(6.03)	(6.58)	(−1.59)	(−1.96)
Initial rating	−0.120	−0.122	0.012	0.018	0.140	0.125
	(−2.87)	(−3.02)	(0.37)	(0.60)	(2.27)	(2.43)
AAA fraction	−0.968	−1.093	0.485	0.470	0.215	0.285
	(−4.27)	(−5.00)	(2.55)	(3.01)	(1.63)	(2.09)
Investment bank	−0.046	−0.066	0.048	0.047	0.027	0.020
	(−2.41)	(−3.57)	(2.39)	(2.05)	(2.94)	(2.43)
Bank size	0.013	0.013	−0.035	−0.047	−0.009	−0.014
	(1.22)	(0.93)	(−2.72)	(−5.21)	(−1.39)	(−3.32)
Bank book-to-market	0.036	−0.000	−0.098	−0.089	0.003	0.010
	(0.89)	(−0.00)	(−1.64)	(−1.52)	(0.16)	(0.59)
Credit enhancement control	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x
Adjusted R^2	0.731	0.710	0.339	0.354	0.161	0.163
Observations	3,804	3,919	3,804	3,919	3,804	3,919

In panel B of Table 7, we report estimation results of regression specifications in which the dependent variables are indicator variables that are set to one when the collateral pool consists of subprime, Alt-A, or second-lien mortgages. We find that high-reputation deals actually had fewer subprime loans but had more Alt-A collateral. The results for second-lien loans are mixed across reputation measures, but second-lien loans are a relatively small part of securitized loans.

One additional advantage of examining the deals contained in ABSnet is that we have direct access to the losses in the collateral pool (i.e., losses in the cash flows received by the deal originating from mortgage delinquencies). It is interesting to assess whether the pools issued by high-reputation underwriters have larger loan losses or whether the differences are solely driven by more aggressive structuring.[27]

Panel C of Table 7 tabulates results of regression models in which the dependent variable is the collateral pool losses. Interestingly, we find that high-reputation underwriters produce deals with worse-performing RMBS

27 It is possible that the impact of reputation on deal performance can be uniquely ascribed to the deal structure. The proportion of senior to junior tranches and the waterfall might mechanically determine different percentage of deal in default for deals with similar losses in the collateral pool.

Panel C: Collateral pool losses and reputation

	Collateral pool losses			
	(1)	(2)	(3)	(4)
High reputation	0.015 (2.35)	0.014 (1.96)		
Top 10 league rank			0.005 (2.65)	0.005 (2.87)
Amount	0.000 (0.07)	−0.001 (−0.16)	−0.000 (−0.01)	−0.001 (−0.23)
Maturity	−0.005 (−0.41)	−0.021 (−1.20)	−0.005 (−0.39)	−0.021 (−1.19)
Initial rating	0.025 (1.50)	0.021 (1.50)	0.025 (1.50)	0.021 (1.51)
AAA fraction	−0.174 (−3.27)	−0.121 (−2.46)	−0.175 (−3.29)	−0.121 (−2.47)
Concentration		0.130 (3.45)		0.133 (3.54)
Percentage California		−0.033 (−0.93)		−0.037 (−1.05)
Percentage Florida		0.192 (3.22)		0.189 (3.20)
Investment bank	0.009 (3.38)	0.008 (2.80)	0.009 (3.48)	0.012 (3.60)
Bank size	−0.012 (−2.45)	−0.010 (−2.38)	−0.012 (−2.58)	−0.009 (−2.32)
Bank book-to-market	−0.043 (−5.16)	−0.039 (−4.86)	−0.042 (−5.00)	−0.037 (−4.66)
Credit enhancement control	x	x	x	x
Vintage by type fixed effects	x	x	x	x
Adjusted R^2	0.603	0.609	0.604	0.609
Observations	3,805	3,785	3,805	3,785

collateral, even after controlling for the type of loans being collateralized and for the correlation in the collateral pool. The finding could indicate that high-reputation underwriters were more subject to the poor incentives tied to the "originate-to-distribute" model, as reported by Keys et al. (2010), Purnanandam (2011), Keys, Seru, and Vig (2012), and Nadauld and Sherlund (2013), including incentives relating to mortgage misreporting found in Piskorski, Seru, and Witkin (2013) and Griffin and Maturana (Forthcoming). Piskorski, Seru, and Witkin (2013) also find that large underwriters, which were diversified beyond the mortgage market, did not engage in less misreporting.

Finally, we revisit the relationship between reputation and securities performance, measured by the proportion of deal in default, for the subsample of RMBS. We report results in panel D, Table 7. We control for collateral quality through the vintage-by-type fixed effects in Column 1 and 5, for collateral

Panel D: Percentage of deal in default and reputation

	Percentage of deal in default							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High reputation	0.115	0.087	0.094	0.075				
	(2.81)	(2.18)	(2.18)	(1.76)				
Top 10 league rank					0.048	0.041	0.046	0.040
					(5.70)	(4.76)	(5.46)	(4.48)
Amount	0.033	0.033	0.024	0.026	0.033	0.032	0.022	0.023
	(3.84)	(3.42)	(2.72)	(2.56)	(5.07)	(4.03)	(2.97)	(2.72)
Maturity	−0.017	−0.010	−0.042	−0.024	−0.045	−0.032	−0.075	−0.050
	(−0.59)	(−0.56)	(−1.77)	(−1.57)	(−1.58)	(−1.53)	(−2.69)	(−2.56)
Initial rating	0.175	0.141	0.170	0.139	0.162	0.135	0.159	0.133
	(4.36)	(6.02)	(4.15)	(5.58)	(4.88)	(6.45)	(4.56)	(5.87)
AAA fraction	0.119	0.344	0.145	0.339	0.107	0.290	0.157	0.303
	(0.61)	(1.81)	(0.75)	(1.81)	(0.60)	(1.72)	(0.89)	(1.83)
Concentration			0.014	−0.144			0.014	−0.146
			(0.13)	(−1.64)			(0.14)	(−1.73)
Percentage California			0.233	0.274			0.270	0.315
			(2.13)	(2.71)			(2.45)	(3.13)
Percentage Florida			0.900	0.669			0.928	0.700
			(6.33)	(5.77)			(5.65)	(4.81)
Investment bank	0.026	0.015	0.033	0.020	0.022	0.009	0.027	0.013
	(2.30)	(1.37)	(2.46)	(1.51)	(2.27)	(0.84)	(2.52)	(1.07)
Collateral pool losses		1.312		1.244		1.279		1.206
		(7.95)		(7.64)		(7.14)		(6.93)
Bank size	−0.004	0.011	−0.003	0.011	−0.017	−0.005	−0.010	−0.000
	(−0.37)	(1.35)	(−0.25)	(1.15)	(−1.84)	(−0.64)	(−1.11)	(−0.02)
Bank book-to-market	−0.020	0.035	−0.036	0.020	0.008	0.055	0.003	0.047
	(−0.78)	(1.34)	(−1.04)	(0.58)	(0.27)	(1.93)	(0.08)	(1.34)
Credit enhancement control	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x
Adjusted R^2	0.518	0.576	0.529	0.580	0.530	0.586	0.542	0.590
Observations	3,804	3,800	3,665	3,665	3,919	3,917	3,780	3,780

This table presents results for a subsample composed by residential MBS (RMBS), for which detailed information about the collateral pool composition is available. In particular, we focus on RMBS deals that are in our main Bloomberg dataset (i.e., ABS Home Equity (subprime) plus residential MBS) and that are covered by ABSnet. In panel A, the dependent variable is either a measure of concentration of state of origination of the mortgages (Concentration) based on the Herfindhal Index, Columns 1 and 2, or the proportion of mortgages in the pool from California (% California), Columns 3 and 4, or the proportion of mortgages in the pool from Florida (% Florida), Columns 5 and 6. In panel B, the dependent variable is an indicator variable equal to one when the collateral pool is primarily constituted by Subprime, Alt-A, or Second Lien mortgages. In panel C, the dependent variable is the percentage losses absorbed by the collateral pool by December of 2012. In panel D, the dependent variable is the percentage of the deal in default relative to the size of the deal. The main variable of interest is either an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score larger or equal to eight, or an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank). Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We also include controls at the underwriter level measured at the deal issuance date: the natural logarithm of the total assets of the underwriter (Bank Size) and the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. The type refers to the type of collateral that is (predominantly) backing the deals, as presented in Table 1. All regression specifications a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. All regression specifications in panels A, C, and D contain vintage (semester) by type fixed effects, whereas regression specification in panel B contain vintage (semester) fixed effects. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample contains deals originated from January 2002 to December 2008. Deals denominated in non-USD currencies are converted into USD using the exchange rate current at the date of issuance. The data are from Bloomberg and ABSNet.

pool losses in Column 2 and 6, for correlation measures in Column 3 and 7, and for all of the above in Column 4 and 8. Deals with more collateral pool losses and more concentration in California and Florida exhibit a higher percentage of collateral in default. Controlling for these differences has a small effect on the size of the reputation measure coefficients, as compared to panel A, Table 2. Results are similar when using the Top 10 League Rank measure of reputation, and in general indicate that the underperformance of high-reputation deals is not driven by poor collateral performance or by deal features that are observable at issuance. We conclude that aggressive structuring must have played a significant role in the underperformance of high-reputation players.

For our full sample, we also examine how certain deal characteristics (measured at issuance) are related to underwriter reputation. Internet Appendix Table A.11 shows that high-reputation underwriters issue larger deals. However, on average there is no support for higher reputation underwriters receiving more favorable ratings or a higher fraction of AAA tranches at closing. If underwriters had the ability to receive higher ratings from a rating agency, one would expect them to receive a larger adjustment beyond the credit rating agency model, but not necessarily an unconditionally larger AAA tranche.[28]

Our results indicate that investors were largely unaware that high-reputation underwriters were producing riskier deals. High-reputation underwriters packaged deals with a slightly higher concentration of collateral from California and less subprime, but more Alt-A, collateral. High-reputation underwriters packaged MBS deals with loans that subsequently underperformed even after controlling for the loan features. Nevertheless, both concentration and poor-quality loan performance cannot fully explain deal performance, suggesting that structuring from high-reputation underwriters was riskier as well.

4. Issuance Amounts and Cross-Sectional Differences in Performance

4.1 Issuance amounts prior to the market collapse

We now examine our second hypothesis that strategic underwriters will continue to issue securities immediately prior to a collapse. Underwriters may do so because they know that the quality of past securities will be revealed, current deals are highly profitable, and the exact timing of the collapse is uncertain. The implication of our model is therefore in contrast with the conventional view of reputation that would predict that underwriters would reduce their production of risky securities to preserve reputation.

First, we hypothesize as to when it became apparent to experts that the structured finance market was in distress. The housing market had stalled by

[28] Because rating agencies are more likely to make positive adjustments on deals with a lower proportion of model generated AAA (Griffin and Tang 2012), it would make more sense for an issuer to take a weak deal structure (which deserves a smaller amount of AAA) and work for an upward positive adjustment. This might leave the issue's proportion of AAA similar to other deals.

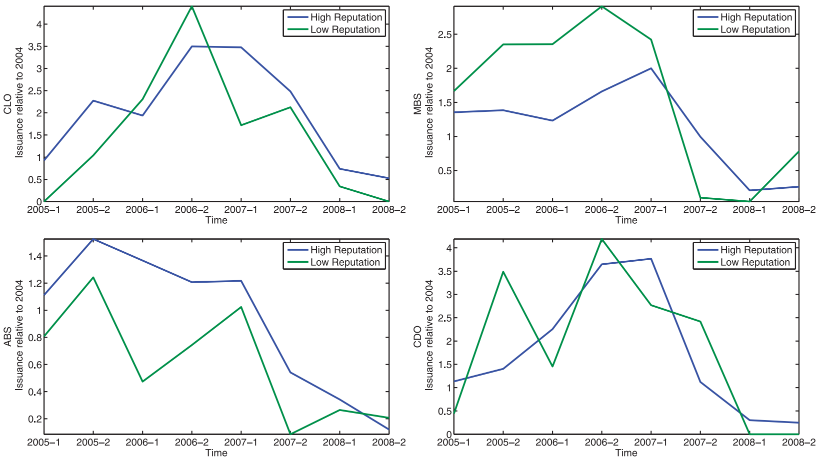

Figure 6
Amounts issued by reputation group around the crisis
This figure shows issuance volumes in each semester from January 2005 through December 2008. Issuances are sampled at semiannual frequency and are separated by reputation score of the underwriter bank. Volumes are scaled by the average semester volume in 2004. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The reputation scores were obtained from Professor Jay Ritter's Web site. The score is a measure of the prestige ranking of IPO underwriters obtained following the method proposed by Carter and Manaster (1990): it is on a 0 to 9 scale, and is based on the pecking order seen in "tombstone" advertisements. Underwriters with a score greater than or equal to eight are deemed "High Reputation;" underwriters with a score lower than eight are deemed "Low Reputation." We match Ritter's dataset to our dataset by name of the underwriter institution. The data are from Bloomberg.

late 2006, and the decline in ABX.HE (an index of CDOs backed by home-equity loans) began in January 2007. On December 11, 2006, Fitch issued a statement in regard to RMBS subprime: "Fitch expects delinquencies to rise by at least an additional 50% from current levels throughout the next year and for the general ratings environment to be negative," (Fitch Ratings 2006). S&P had a conference call with their clients (the banks) to discuss deteriorating RMBS performance on February 15, 2007 (Shenn 2007). That was followed by one from Moody's on February 17, 2007 (Tennant 2006).[29] Hence, it seems that by early 2007 it was increasingly clear to industry insiders (but not to those outsiders who did not understand the subtleties of structured finance) that all mortgage-related collateral was deteriorating.

For this reason, we examine issuer activity in 2007. Figure 6 plots issuance in each semester following 2005 relative to the average semester issuance in 2004. We are, in particular, interested in examining whether the high- and low-reputation underwriters decreased their issuances in the first half of 2007. High-reputation underwriters brought more CDOs and nonagency MBS to the

29 More announcements surrounding RMBS from the rating agencies followed in March. A notable quote (Mitchell 2007) on March 3, 2007 states that, "the legs that powered the CDO machine for the last three years have fallen off."

market in the first half of 2007 than in all previous year-halves. ABS and CLO issuance by high-reputation issuers in the first part of 2007 is only slightly off from the 2006 peaks. High-reputation underwriters did not withdraw from the structured finance spaces at a higher pace than did low-reputation underwriters. In fact, in the MBS and the ABS market, low-reputation underwriters did not issue securities in the second half of 2007 (probably because they could not generate sufficient demand), whereas high-reputation underwriters still had substantial issuances. The large volume in the first and second half of 2007 in the MBS, ABS, and CDO markets is remarkable considering that these markets nearly disappeared by the end of 2007.

4.2 Burning reputation in distress or building poor securities?

Titman and Tsyplakov (2010) find that commercial mortgage originators package worse collateral when they are in distress. It is then reasonable to ask whether the issuance of poorly performing securities might concentrate in 2007, especially in the banks that were in distress.

In Figure 7, we compare the percentage of deal in default as of December 2010 for securities issued in 2005 and 2006, relative to that of securities issued in 2007. (Abbreviation codes for the bank names can be found in Internet Appendix Table A.2.) Across the entire structured finance market, we observe a remarkably stable pattern: underwriters issued securities in 2005 and 2006 that had a similar performance ranking to those issued in 2007. Thus, we do not find evidence that underwriters built and then burned their reputation. The rank correlation between the performance of the two vintages is 0.901 and thus would seem to contradict the view that bad securities were issued only when banks were in distress.

The persistence in performance may be explained by specialization within certain areas of structured finance. To examine this possibility, we estimate bank fixed effects from a regression specification similar to the one shown in Column 6 of Table 2 in which the dependent variable is the proportion of deal in default, and we control for vintage and security type (Vintage by Type Fixed Effects), as well as for specific securities' characteristics (except for reputation). The bank fixed effects then can be interpreted as the abnormal performance of the bank after controlling for the characteristics of the securities they issued. Panel B of Figure 7 examines the relation between bank fixed effects from 2005–2006 relative to fixed effects in 2007. The persistence between the two periods is slightly weaker than in panel A, but there is still a strong rank correlation of 0.61 between the two periods.

It is relevant to know if the persistence in performance is related to one particular market. Internet Appendix Figure A.6 shows that for raw performance there is a positive correlation between the 2005–2006 and 2007 period in MBS, ABS, and CDOs. Therefore, the persistence in bank performance (with or without controls for the securities' characteristics) is not generally consistent

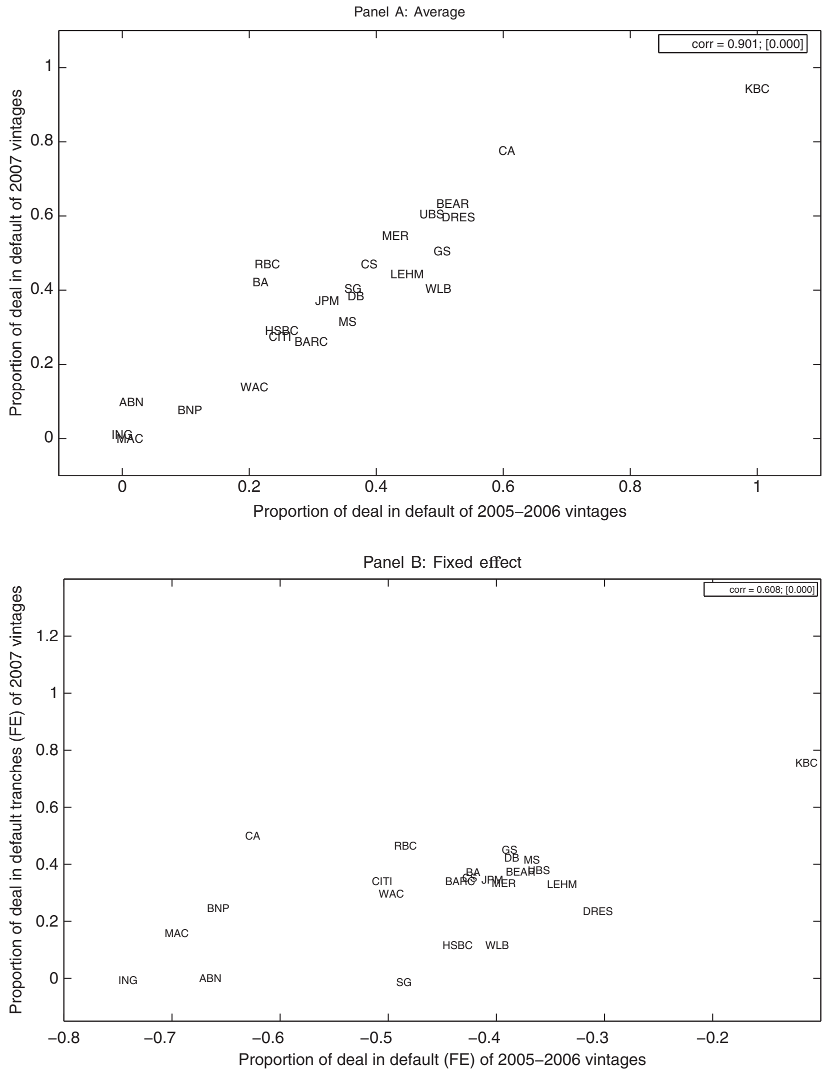

Figure 7
Overall performance by banks around the crisis
This figures shows how the performance (proportion of deal in default) of the securities issued during 2005 and 2006 is related to the performance of the securities issued in 2007, around the beginning of the financial crisis. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal and aggregated at the underwriter level. Panel A presents results for the full sample average performance. Panel B presents a plot similar to that reported in panel A but wherein averages are replaced by bank fixed effects. Fixed effects are estimated from separate regressions for the two vintages of 2005–2006 and of 2007. Each regression is similar to that reported in Column 6, panel A, Table 2, except that we do not include the reputation variable. The data are from Bloomberg.

with the explanation that banks only produced poor securities in 2007, when they may have needed to unload securities.

We more formally test the hypothesis that banks produce poor securities when in trouble by including, in the spirit of Titman and Tsyplakov (2010), some measures of the underwriter's stock returns in our analysis. In particular, we include the bank stock return in the quarter and semester before issuance of the security as independent variables in our performance regression. Because banks might engage in this type of activity only when experiencing extreme movements in their equity values, we also include indicator variables equal to one when the return is lower than -15% in the quarter or semester prior to security issuance, as in Titman and Tsyplakov (2010). As an alternative measure of bank performance, we also include the underwriter five-year CDS spread as of the issuance date. We present the results of these analyses in Table 8. We find no evidence that security performance is related to the distress of the firm. More importantly, the relationship between high reputation and deal performance is unaffected by the inclusion of the bank's past stock returns or by the inclusion of the bank CDS spread. In summary, high-reputation banks issued poorly performing securities regardless of whether they were experiencing periods of distress.

4.3 Committed or opportunistic banks?

Our theoretical analysis allows for scenarios in which underwriters are committed to the interest of their clients at their own expense. In this section we take a closer look at individual bank performance to ascertain whether there is evidence of any such behavior. In particular, a committed bank would have issued "good" securities and would have withdrawn from the market when it was apparent that the market was collapsing.

In panel A of Table 9 we rank all the banks in our sample (with at least five deals and total issuance of $1 billion) and order them according to their fixed effect from a regression of the proportion of deal in default that controls for vintage by type fixed effects and issuer and security characteristics. In this way, we sort banks based on the performance that cannot be attributed to the type of securities they created.[30] Banks that completed more than twenty deals in bold to separate the smaller issuers from those who had a more significant presence in the market.

In general, we find that large and well-known banks sit at the top of the ranking (worst performers). Notably, among the ten banks with the worst abnormal performance, eight are of high reputation (8 or 9). Conversely, for the ten banks with the best performance (bottom of the table), only two banks (Santander and Mediobanca, with small volume) rank at eight or above. We seek

[30] Because we do not want to lose any data, especially around 2006 and 2007, for this part of the analysis we consider all bank year observations regardless of whether there is an IPO ranking measure in any particular year. In the table we report all these deals and pair them with the reputation measure that is available to us.

Table 8
Reputation and bank recent performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High reputation	0.078	0.026	0.078	0.025	0.079					
	(4.49)	(1.53)	(4.50)	(1.51)	(4.54)					
Top 10 league rank						0.041	0.038	0.042	0.038	0.047
						(5.31)	(5.00)	(5.48)	(4.94)	(6.09)
Bank size	−0.004	−0.011	−0.003	−0.011	−0.009	−0.018	−0.003	−0.018	−0.003	−0.016
	(−0.60)	(−1.39)	(−0.43)	(−1.43)	(−1.15)	(−1.83)	(−0.34)	(−1.82)	(−0.38)	(−1.87)
Bank book-to-market	0.000	−0.003	0.004	−0.005	0.003	−0.001	−0.003	−0.001	−0.004	0.007
	(0.01)	(−0.66)	(0.63)	(−0.97)	(0.36)	(−0.18)	(−0.48)	(−0.21)	(−0.64)	(1.28)
Bank 3-month return	0.063					0.031				
	(2.19)					(1.11)				
Bank 3-month return <-0.15		−0.002					−0.009			
		(−0.11)					(−0.54)			
Bank 6-month return			0.072					0.015		
			(2.47)					(0.47)		
Bank 6-month return <-0.15				0.019					0.003	
				(1.60)					(0.25)	
Bank 5−year CDS					−0.018					−0.033
					(−1.08)					(−2.18)
Deal controls	x	x	x	x	x	x	x	x	x	x
Credit enhancement control	x	x	x	x	x	x	x	x	x	x
Vintage by type fixed effects	x	x	x	x	x	x	x	x	x	x
Adjusted R^2	0.498	0.490	0.499	0.490	0.504	0.493	0.498	0.493	0.498	0.505
Observations	10,796	11,045	10,725	11,045	10,099	10,965	10,861	10,878	10,861	9,667

This table reports estimation results of regression models in which the dependent variable is the proportion of the deal in default as of December 2010. The main variable of interest is either an indicator variable (High Reputation) set equal to one for deals with an underwriter IPO reputation score larger or equal to eight, or an indicator variable set equal to one when the underwriter belongs to the top ten of the league rank table of fixed income desks (Top 10 League Rank). Other control variables are the natural logarithm of the size of the deal in billion dollars (Amount), the natural logarithm of the maturity of the securities in years (Maturity), the value-weighted rating of the securities comprising a deal as of the date of issuance (Initial Rating), the fraction of AAA-rated securities as of the issuance date relative to the size of the deal (AAA Fraction), an indicator variable that identifies deals that are backed, in part or in full, by positions in CDS contracts (Synthetic), and an indicator variable equal to one for securities that are produced by an investment bank (Investment Bank). We group these variables into a group "Deal Controls" and omit their coefficients to save space. We also include controls at the underwriter level: the natural logarithm of the total assets of the underwriter (Bank Size), the ratio of book equity capital to the market value of the underwriter (Bank Book-to-Market), the bank stock return in the quarter and semester before issuance of the security (Bank 3-month Return and Bank 6-month Return), indicator variables equal to one when the return is lower than -15% in the previous quarter or semester (Bank 3-month Return $< -15\%$ and Bank 6-month Return $< -15\%$), and finally the five year CDS spread as of the issuance date (Bank 5-year CDS). Estimated coefficients are reported along with t-statistics based on standard errors clustered by vintage (semester) by type, in parenthesis. All regression specifications contain vintage (semester) by type fixed effects, and a set of indicator variables that are set equal to one when the deal has one of the following credit enhancements: collateral account, cross-collateralization, insurance wrap, letter of credit, overcollateralization, reserve account, spread account, and subordination. A constant is estimated but not reported. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

Table 9
Performance by banks

	Rep	Issuance volume	Number of deals	Proportion in default		Proportion in default FE			Volume change
				Average	FE	00–06	05–06	07	
KBC Bank	5.0	18.1	20	0.329	0.239	0.225	−0.113	0.755	0.158
Daiwa Securities	8.0	31.0	40	0.277	0.134	−0.141	−0.564		−0.247
Wells Fargo Securities	7.3	5.5	20	0.567	0.114	−0.057		0.904	1.000
Lehman Brothers	8.1	995.8	1,597	0.301	0.069	0.034	−0.339	0.329	−0.093
UBS	8.1	480.8	803	0.370	0.059	0.017	−0.361	0.379	−0.297
Morgan Stanley	9.0	761.0	1,248	0.251	0.056	−0.003	−0.367	0.416	0.327
Deutsche Bank	9.0	1,089.4	1,401	0.239	0.048	−0.008	−0.386	0.422	−0.095
Goldman Sachs	9.0	641.4	935	0.363	0.048	−0.022	−0.388	0.451	−0.138
Bear Stearns	8.0	954.5	1,471	0.342	0.037	−0.014	−0.378	0.373	−0.348
Bank of America	8.0	1,221.1	1,181	0.142	0.034	−0.014	−0.421	0.371	−0.364
Merrill Lynch	9.0	720.8	1,008	0.340	0.033	−0.009	−0.393	0.334	0.052
Credit Suisse	9.0	1,220.0	1,701	0.273	0.030	−0.018	−0.425	0.353	−0.084
Barclays Bank	8.0	588.4	609	0.159	0.012	−0.036	−0.433	0.341	−0.136
JP Morgan Chase	9.0	1,316.4	1,466	0.195	0.008	−0.042	−0.404	0.346	−0.089
RBC Capital Markets	7.3	19.1	54	0.203	−0.006	−0.090	−0.484	0.464	−0.244
Citigroup	9.0	1,330.5	1,590	0.185	−0.008	−0.064	−0.506	0.340	0.345
Scotia Capital	7.0	3.5	16	0.006	−0.011	−0.062	0.260		−1.000
Commerzbank	7.0	39.3	32	0.015	−0.022	−0.038	−0.257		1.000
Dresdner Bank	7.0	43.1	110	0.384	−0.022	−0.041	−0.306	0.235	−0.279
Credit Agricole	7.0	84.5	199	0.389	−0.031	−0.129	−0.625	0.499	−0.242
Jefferies & Co	5.5	10.5	36	0.323	−0.033	−0.170			0.000
Wachovia Securities	7.0	349.5	473	0.203	−0.034	−0.081	−0.497	0.296	−0.332
Friedman Billings Ramsey	5.0	9.2	23	0.360	−0.044	−0.094	−0.453		−1.000
HSBC	8.8	173.9	331	0.226	−0.055	−0.029	−0.436	0.117	0.610
Societe Generale	7.0	101.0	165	0.134	−0.074	−0.073	−0.485	−0.013	−0.264
McDonald Investments	5.2	1.0	7	0.034	−0.078	−0.140	−0.216	0.288	1.000
Santander	8.1	122.2	49	0.048	−0.113	−0.128	−0.705	0.074	1.000
Suntrust Cap Mkts	6.1	3.8	16	0.056	−0.114	−0.190	−0.573	0.426	−0.668
BNP Paribas	7.0	179.9	246	0.040	−0.121	−0.188	−0.657	0.246	0.987
Mediobanca	8.0	7.4	8	0.000	−0.136	−0.181	−0.780		−1.000
Macquarie Bank	6.0	30.5	66	0.004	−0.139	−0.213	−0.696	0.158	−0.072
BB&T Capital Markets	6.5	2.1	18	0.000	−0.151	−0.325	−0.678	0.156	−0.275
BMO−Nesbitt Burns	6.8	7.7	19	0.025	−0.159	−0.203	−0.607	0.021	−0.105
Investec Bank	7.0	3.2	17	0.000	−0.174			−0.096	−0.251

This tables presents summary statistics calculated for individual underwriters in each market in which they operate. We present the average reputation during the sample period, the total issuance volume (in billion), the number of deals, the average proportion of deal in default, the bank fixed effects estimated from a regression of proportion of deal in default similar to that reported in Column 5, panel A, Table 2, wherein we do not include the reputation variable, the bank fixed effects from different subperiods (2000 to 2006, 2005 to 2006, and 2007), and, finally, the change in issuance volume from 2005–2006 to 2007. The change in volume is constructed as the ratio of the total volume in 2007 to the average volume in 2005 and 2006. The table presents results for the full sample (Overall). We report performance in the individual markets in the Internet Appendix Table A.12. The data are organized at the deal level, so that all securities (i.e., tranches) that are backed by the same assets are grouped together into a deal. The names of the banks that issued at least twenty deals during the sample period appear in bold. The sample is from January 2000 to December 2010, and the data are from Bloomberg.

confirmation of the results reported in the previous sections by performing a Fisher's Exact test to determine whether the worst ten banks have a statistically significantly higher proportion of high-reputation banks than do the ten top performers and find a p-value of 0.032 despite the small sample size. The underperformance is not driven by a few banks: high-reputation banks tend to issue worse securities.

We also examine, and report in the last column of the table, the change in issuance volume in 2007 relative to each bank's 2005–2006 average volume.

The last column of panel A, Table 9, shows no particular trend. If we sort observations based on the change in issuance volume in 2007 relative to 2005–2006, we find five high-reputation banks among the ten banks with the largest decreases in 2007 issuance volume. Of these, Mediobanca and Daiwa had extremely few issuances. Lehman, Bear Sterns, and UBS all experienced financial difficulties in 2007.[31] In Appendix Table A.12 panels B-E we examine the performance of issuances by banks in CLO, MBS, ABS, and CDO, separately. Overall, we fail to find evidence of a high-reputation underwriter that fits the traditional notion of a commitment type.

5. Conclusion

It is common to assume that high-reputation firms make good securities to maintain their long-run reputation. We develop a theoretical model that shows where this intuition can break down. Empirically, we find that structured finance securities issued by high-reputation underwriters did not outperform, and, in fact, performed worse in all years of the financial crisis. The underperformance of high-reputation underwriters is present across the entire structured finance market and in particular in the more complex MBS, ABS, and CDO spaces and with a variety of collateral-type controls. We cannot completely rule out the possibility that high-reputation underwriters simply packaged different deals. Nevertheless, we find no evidence that the perceived risk at issuance embedded in yields drove the underperformance. Underwriters perceived to be of high-reputation collateralized loans of lower quality and slightly higher concentration, although these features alone cannot explain their poor performance.

Our model suggests that underwriters will continue to issue securities prior to an asset's collapse because they know the quality of past securities will be revealed, deals are highly profitable, and the exact timing of the collapse is uncertain. Even well after housing and subprime collateral began to lose value in early 2007, we find that high-reputation underwriters issued record or near-record levels of MBS, ABS, and CDOs. Apart from our model, an alternative and more charitable explanation for our empirical findings is that high-reputation underwriters were systematically unlucky in selecting collateral assets that they were including in their structured finance deals.

Our model and findings largely contrast with the common view, as well as much empirical evidence, showing that high underwriter reputation is uniformly beneficial for a bank's clients. Nevertheless, it is not fruitful to simply fault complexity and/or high reputation. Complexity is often used to reach Pareto-dominating allocations, and our model shows how, in many

[31] A popular story described by the media and industry is that, in response to troubling signs in the market in late 2006, JP Morgan largely backed out of structured finance security issuance (Barr 2008; Wilson and Kerr 2009). In contrast to this description, we see only a small decrease in volume for JP Morgan in 2007.

states of the world, investors are better off dealing with high-reputation banks. Although our analysis focuses on the supply-side for structured products, further understanding the determinants of the demand for structured products represents an important topic for future research. We also hope to see further dialogue on the role of reputation, conflicts of interest, and complexity in financial markets.

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