The Rise and Fall of Demand for Securitizations*

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Abstract

Collateralized debt obligations (CDOs) and private-label mortgage-backed securities (MBS) backed by nonprime loans played a central role in the recent financial crisis. Little is known, however, about the underlying forces that drove investor demand for these securitizations. Using micro-data on insurers' and mutual funds' bond holdings, we find considerable heterogeneity in investor demand for securitizations in the pre-crisis period. We argue that both investor beliefs and incentives help to explain this variation in demand. By contrast, our data paints a more uniform picture of investor behavior in the crisis. Consistent with theories of optimal liquidation, investors largely traded in more liquid securities such as government-guaranteed MBS to meet their liquidity needs during the crisis.

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Collateralized debt obligations (CDOs) and private-label mortgage-backed securities (MBS) backed by nonprime loans were at the heart of the recent financial crisis. Issuance of these securitizations grew exponentially from 2003 to early 2007 before collapsing in mid-2007. Secondary market prices for these products fell precipitously throughout late 2007 and 2008, generating large losses for financial intermediaries and helping to trigger a full-blown systemic crisis in late 2008.

Despite general agreement on this broad narrative, there is little consensus about the deeper forces that drove the rise and subsequent fall in investor demand for CDOs and nonprime MBS. Broadly speaking, explanations for the pre-crisis run-up in demand point to distortions that affected either investor beliefs or incentives. Beliefs-based explanations argue that a misunderstanding of the risks of investing in securitizations helped drive investor demand, while incentives-based explanations emphasize agency problems between professional investors and their principals.[1]

Explanations for the collapse in demand during the crisis argue that either fire sales or a buyers' strike amplified an initial fundamental shock due to declining home prices. In fire sales-based explanations, the fundamental shock was amplified by forced sales from investors with high valuations to others with low valuations, while in buyers' strike-based explanations, it was amplified by a refusal to trade due to adverse selection or other frictions.[2]

While theoretical explanations for the boom and bust abound, empirical work has been hampered by a lack of data on the investors who bought securitizations.[3] In this paper, we use new micro-data on mutual funds' and insurance companies' holdings of fixed-income securities to shed light on the forces that drove the rise and fall of demand for securitizations. Specifically, we study the quarterly fixed-income holdings of mutual funds and insurance companies from 2003–2010. These institutions are two of the largest investors in credit securities, owning close to 30% of all corporate

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[1] See Coval, Jurek, and Stafford (2009) and Gennaioli, Shleifer, and Vishny (2012) for beliefs-based explanations. For incentive-based explanations, see Rajan (2005), Acharya and Richardson (2009), and Merrill, Nadauld, and Strahan (2014).

[2] For theoretical models of fire sales, see Shleifer and Vishny (1992, 2011), Kiyotaki and Moore (1997), Lorenzoni (2008), Brunnermeier and Pedersen (2009), Geanakopolos (2009), Stein (2012), Brunnermeier and Sannikov (2014), and Dávila (2014). See Dang, Gorton, and Holmstrom (2013), Hanson and Sunderam (2013), Milbradt (2012), and Morris and Shin (2012) for models of buyers' strikes.

[3] For instance, He, Khang, and Krishnamurthy (2010) use Flow of Funds data to assess the balance sheet adjustment of different financial intermediaries in 2008. However, as the authors note, the Flow of Funds lacks the granularity needed to track holdings of private securitizations. Similarly, Erel, Nadauld, and Stulz (2013) explore banks' private securitization holdings, but cannot explore variation across the type of underlying collateral due to the limits of bank regulatory data.

bonds and private securitizations.[4] We use this data to pinpoint investor characteristics that were associated with greater holdings of securitizations and to describe investors' trading behavior in securitizations. We then interpret our findings in light of the theoretical literature.

Our analysis focuses on nontraditional securitizations, which consisted of CDOs and MBS backed by nonprime home mortgages. While traditional securitizations backed by prime residential mortgages, commercial mortgages, and consumer debt had existed for decades, nontraditional securitizations were a more recent innovation. And, as Figure 1(a) shows, the rapid growth in securitization during the 2003–2007 boom was concentrated in nontraditional products.

We begin by showing that during the 2003–2007 boom there was considerable heterogeneity across investors in their demand for nontraditional securitizations. At a macro level, while both insurers and mutual funds increased the share of their portfolios allocated to nontraditional securitizations, these increases did not keep pace with the broader credit market—i.e., as issuance boomed, insurers and mutual funds became increasingly underweight relative to the market. Within mutual funds and insurers, a simple variance decomposition of our micro-level holdings data indicates that most variation in nontraditional securitization holdings was variation across investors as opposed to common variation over time.

Which investor characteristics were associated with larger holdings of nontraditional securitizations? We start with mutual funds and estimate cross-sectional regressions relating portfolio weights in nontraditional securitizations to a variety of fund and manager characteristics. Among mutual funds with the same objective, fund manager experience stands out relative to other fund characteristics: experienced managers invested significantly less in nontraditional securitizations than inexperienced managers.

What explains the relationship between fund manager experience and securitization holdings? Perhaps inexperienced mutual fund managers faced incentives that were more misaligned with those of their shareholders than the incentives faced by experienced managers. We find little evidence of this in our data: inexperienced and experienced managers faced similar performance-flow relationships, a common proxy for the strength of the risk-taking incentives faced by managers. In

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[4] According to the Flow of Funds, as of 2007Q2, the total outstanding amount of corporate and foreign bonds, which include privately-issued securitizations, was $10.88 trillion. Of this, mutual funds (excluding money market mutual funds) owned $0.84 trillion (7%), and insurers (both life and property and casualty) owned $2.13 trillion (20%).

addition, we examine pairs of regular mutual funds and variable annuity funds that had the same investment objective and were run by the same fund manager. Because they are sold as part of an insurance product, variable annuity funds face weaker performance-flow relationships and therefore risk-taking incentives, than regular mutual funds. However, we find that there was little difference in the holdings of nontraditional securitizations by regular mutual funds and variable annuity funds run by the same manager.

Alternatively, as suggested by the growing literature on reinforcement learning, the greater demand of inexperienced managers may have been due to differences in beliefs.[5] Consistent with this, we find that managers who were active during the credit market disruptions following the 1998 Russian default invested significantly less than other managers. Personal experience during the market disruption mattered: the effect appears to be driven by managers whose funds suffered poor returns or heavy outflows in 1998. Furthermore, prior experience appears to have moderated optimism about house prices during the boom. We find that funds located in MSAs with stronger pre-crisis home price growth invested more heavily in securitizations, but there is suggestive evidence that this effect was weaker for experienced managers. Overall, these results lend support to the idea that beliefs, shaped in part by prior firsthand experiences, played an important role in driving mutual fund demand for nontraditional securitizations.

Of course, these results do not rule out incentives-based explanations for the pre-crisis surge in demand for nontraditional securitizations. Incentive misalignments may simply not have been sufficiently severe for mutual funds. To analyze a setting where incentive misalignments may have been more important, we turn to our data on insurance companies. Insurers are large regulated financial intermediaries that were perhaps more likely to face the kinds of incentive conflicts that the literature has highlighted.

We follow a similar procedure, estimating cross-sectional regressions relating insurers' portfolio weights in nontraditional securitizations to a variety of firm characteristics. We find that holdings of nontraditional securitizations were higher among larger insurers and insurance companies that had fixed income portfolios managed by external managers. Among the largest 100 insurers,

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[5] See, for instance, Greenwood and Nagel (2009), Malmandier and Nagel (2011, 2014), and Campbell, Ramadorai, and Ranish (2013).

which together comprise almost 90% of total assets, holdings of nontraditional securitizations were concentrated among poorly capitalized insurers. These findings are consistent with the notion that misaligned incentives played a role in driving insurer demand for nontraditional securitizations. Among small insurers, the key principal-agent relationship was between the insurer, which may have lacked the expertise necessary to directly invest in securitizations, and external portfolio managers. Among larger insurers, the key principal-agent relationship was between creditors and equity holders.

How did investor demand for securitizations change after the onset of the crisis in mid-2007? For both mutual funds and insurance companies, we find that trading in nontraditional securitizations declined through the boom from 2003–2007 and was extremely low during the 2007–2009 bust. In contrast, trading in corporate bonds remained relatively stable from 2003–2010. This is consistent with the buyers' strike narrative, which emphasizes market freezes due to adverse selection or other frictions. However, we also show that mutual funds with large holdings of nontraditional securitizations suffered larger outflows during the crisis. Consistent with theories of fire sales where investors follow optimal liquidation strategies, funds met these redemptions primarily by selling liquid government-guaranteed MBS and not by selling illiquid nontraditional securitizations.

Putting it all together, our micro-data on investor holdings of securitizations paints a multifaceted picture of the boom in nontraditional securitization and a more uniform picture of the bust. In the boom, there was significant heterogeneity across investors in the demand for nontraditional securitizations. Among mutual funds, beliefs appear to have been a key driver of holdings of nontraditional securitizations, while incentives appear to have played an important role among insurers. In the bust, investors behaved similarly. They traded very little in nontraditional securitizations, preferring to transact in more liquid securities to meet their liquidity needs.

A few brief notes on our approach are in order before proceeding. First, the aim of this paper is not to advance one specific narrative of the financial crisis. Indeed, it seems unlikely that any one theory alone can completely explain such a complex phenomenon. Second, our analysis is largely descriptive. In the absence of clean natural experiments, we are generally not able to definitively identify causal effects. Instead, we pursue a series of descriptive tests that help shed light on the forces that drove investor demand. We carefully consider factors that may confound our interpretations of these tests, but ultimately our tests remain descriptive. Overall, our goal is to document a series of robust stylized facts that can inform future theoretical and empirical work about the crisis. In this way, our approach is similar to that of Griffin, Harris, Shu, and Topalugua (2011), who describe investor behavior in the dot-com era, and Krishnamurthy, Nagel, and Orlov (2014), who study runs on short-term debt in the crisis.

The plan for the paper is as follows. Section I provides background on traditional and nontraditional securitizations. Section II outlines competing theoretical narratives of the surge and subsequent collapse in demand for nontraditional securitizations. Section III explains the data sources we use in the paper. Section IV uses our holdings data to explore the drivers of the boom, while Section V sheds light on the mechanics of the bust. Section VI offers some concluding observations.

I. Background on Securitization

This section provides a brief background on securitization. Securitizations are created by pooling and tranching—assembling a pool of cash-flow-generating financial assets such as loans or debt securities and then issuing claims of various priorities backed by that pool.

In the United States, the securitization of home mortgages dates to the late 1960s and early 1970s, when various Government Sponsored Enterprises (GSEs), corporations that were implicitly or explicitly guaranteed by the U.S. government, began issuing securities backed by residential mortgage pools. Only "conforming" mortgages, which must meet certain requirements for size, credit scores, loan-to-value ratios, and documentation, are eligible to be included in GSE mortgage pools. Because the GSEs guarantee the timely payment of principal and interest on the underlying loans, investors in *GSE-guaranteed mortgage-backed securities* (*GSE MBS*) bear little credit risk. The market for GSE MBS grew exponentially during the 1980s and 1990s, eventually overtaking the market for U.S. Treasuries to become the single largest debt market in the U.S. (Fabozzi [2005]).

The 1980s saw the advent of several types of private securitizations that were not backed by the U.S. government, which we broadly refer to as "traditional securitizations." They include:

- *Commercial Backed Mortgage Securities (CMBS)*: The securitization of commercial mortgages into CMBS was pioneered by investment banks in the early 1980s. However, this market grew to prominence only in the early 1990s when the Resolution Trust Corporation began using it to sell off the commercial real estate loans of failed depository institutions. The CMBS market grew rapidly throughout the 1990s and 2000s.
- *Consumer Asset-Backed Securities (ABS)*: The securitization of non-mortgage consumer debt, including credit card, automotive, and student loans, began in the late 1980s. These markets developed rapidly, and by 2000 over 30% of outstanding consumer debt had been

securitized according to the Flow of Funds. The market for consumer ABS grew more slowly from 2003–2007, with the fraction of consumer debt that had been securitized falling to 25% by 2007Q2.

- *Prime non-GSE RMBS***:** Beginning in 1977, investment banks began securitizing prime "jumbo" residential mortgages that conformed to all GSE MBS criteria other than the size limit (Fabozzi [2005] and Gorton [2008]).

The boom in securitization from 2003–2007 prominently featured new types of securitizations, which developed much later than these traditional securitizations. We label this second set of securitizations "nontraditional." They include:

- *Nonprime RMBS*: The securitization of subprime and Alt-A home mortgages began in the mid-1990s. Alt-A mortgages are not prime due to high loan-to-value ratios or a lack of sufficient documentation. Subprime mortgages are not prime because the borrower has a low credit score. The origination and securitization of nonprime mortgages exploded during the boom from 2003–2007.[6]
- *Collateralized Debt Obligations (CDOs)*: CDOs are securitizations backed by a portfolio of fixed income assets. CDOs are classified as collateralized bond obligations (CBOs), collateralized loan obligations (CLOs), or ABS CDOs. CBOs are collateralized by corporate bonds and were the most common type of CDO until the late 1990s and early 2000s. However, this market grew slowly during the 2003–2007 period. CLOs invest primarily in senior secured loans to highly leveraged firms. CLO issuance boomed from 2003–2007. ABS CDOs use bonds from other securitizations as collateral. ABS CDOs, particularly those using nonprime RMBS as collateral, grew explosively over the course of the boom. Many of the most dramatic losses by large financial intermediaries announced during 2007 and 2008 were linked to ABS CDOs**.**[7]

[6] See Fabozzi (2005), Gorton (2008), and Ashcraft and Schuermann (2008) for further background on nonprime MBS.

[7] See Shivdasani and Wang (2013) for further background on CLOs. See Barnett-Hart (2009) and Cordell, Huang, and Williams (2012) for more detail on ABS CDOs.

II. Narratives of the Boom and Bust

In this section, we discuss different explanations for the surge and subsequent collapse in demand for nontraditional securitizations. Our aim in this paper is not to advance a specific narrative of the crisis or to definitively test one narrative against another. Instead, we approach the data with a flat prior, with the goal of documenting a series of robust stylized facts that can be used to refine these different explanations and inform future research about the forces that drove investor demand for securitizations.

A. Narratives of the boom

Explanations of the pre-crisis surge in demand for securitizations can be grouped into two broad categories: those that highlight distorted beliefs and those that highlight distorted incentives.[8]

A.1 Beliefs

In the context of the 2003–2007 securitization boom, beliefs-based explanations argue that investors misunderstood the risks of investing in nontraditional securitizations. Many have suggested that investors treated all AAA-rated securitizations as though they were virtually risk-free. For instance, Gerardi, Lehnert, Sherlund, and Willen (2008) and Gennaioli, Shleifer, and Vishny (2012) argue that investors neglected the risk of a substantial nationwide downturn in house prices and therefore believed that a diversified exposure to residential mortgages was almost riskless. Coval, Jurek, and Stafford (2009) suggest that investors focused on credit ratings which reflected expected losses but neglected the systematic risk embedded in securitizations. Ashcraft, Goldsmith-Pinkham, and Vickery (2010) and Rajan, Seru, and Vig (2013) argue that investors and rating agencies failed to update their models of loan default in the face of deteriorating loan underwriting standards, thus neglecting the risks associated with lending to riskier households.

Simple versions of the distorted-beliefs explanation for the boom tend not to emphasize heterogeneity among investors or across securities. In these simpler narratives, all investors incorrectly assessed the risks of securitizations, driving up the prices of all AAA-rated securitizations

[8] We do not focus on explanations of the boom that emphasize demand for “money-like” assets as in Caballero and Farhi (2013) and Gorton and Metrick (2010a, b). Similarly, we bypass explanations focusing on the role of international demand for safe assets as in Bernanke (2005), Bernanke, Bertaut, DeMarco, and Kamin (2011), Caballero (2009), and Shin (2012). Since our data only included U.S.-based investors, it is not geared towards addressing these questions.

in lock step. In more nuanced versions of this narrative, particular subsets of investors may have been more susceptible to distorted beliefs. For instance, Gennaioli, Shleifer, and Vishny (2012) argue that unsophisticated investors were shocked by the swift decline of nationwide home prices. Consistent with this, anecdotal accounts suggest that demand from smaller, less sophisticated investors such as small insurance companies and pension funds played an important role in fueling the boom.

A.2 Incentives

Incentives-based narratives of the boom emphasize agency problems within the financial sector. In these explanations, sophisticated actors within financial institutions correctly understood that securitizations were risky. However, because of the incentives they faced, these agents purchased more securitizations than their ultimate principals would have if acting on their own behalf. These explanations differ primarily in where they locate the critical agency conflict within the financial system. Furthermore, incentives-based explanations frequently highlight heterogeneity across investors because some may have faced worse incentive distortions than others.

For instance, the mutual fund literature typically argues that agency problems between fund managers and investors stem from the performance-flow relationship (Chevalier and Ellison [1997]). Since expected fund inflows are a convex function of past performance, managers face incentives to take on risk to maximize their expected future compensation, even if this does not maximize expected fund returns. Thus, according to the incentives view, the more convex the performance-flow relationship a fund manager faced, the larger her holdings of securitizations would have been.

This type of incentive problem may also arise for insurers because they sometimes outsource the management of their portfolios. Because insurers cannot perfectly observe risk taking by external assets managers and risk-adjust their performance, these managers may have an incentive to boost perceived performance by taking excessive risks. This problem may have been particularly acute for highly-rated securitizations because they tend to perform well outside of adverse, low-probability economic states (Acharya, Pagano, and Volpin [2013] and Adrian and Shin [2014]).

Agency problems between external capital providers and managers at financial institutions can also take the form of risk-shifting as in Jensen and Meckling (1976). In these narratives, managers acting on behalf of existing shareholders purchased highly-rated securitizations to capture the yield associated with bearing tail risk, increasing the expected payoff to equity, while reducing total firm value at creditors' expense (Landier, Sraer, and Thesmar [2011]).[9,10] These problems may have been exacerbated by poorly-designed regulatory capital rules that did not properly capture systematic risk, giving regulated intermediaries incentives to load up on highly-rated securitizations (Acharya and Richardson [2009]; Merrill, Nadauld, and Strahan [2014]). For instance, if the conflict between equity and creditors is stronger for less well-capitalized insurers, they may have been more likely to hold nontraditional securitizations.[11]

Note that both the distorted beliefs and incentives narratives provide reasons why some investors may have had elevated demand for nontraditional securitizations. The large literature on limits to arbitrage initiated by DeLong, Shleifer, Summers, and Waldmann (1990a) and Shleifer and Vishny (1997) suggests that other investors may have been reluctant to aggressively lean against these demand shocks. Indeed, they may even have had incentives to "ride" a bubble rather than leaning against it as in DeLong, Shleifer, Summers, and Waldmann (1990b) and Abreu and Brunnermeier (2002). The limited offsetting response by arbitrageurs would then explain why these demand shocks raised equilibrium prices, increasing incentives for issuance.

B. Narratives of the bust

In contrast to the disagreement that exists about the drivers of the boom in securitizations, there is wider consensus about the market collapse from mid-2007 to 2009. The frictionless null hypothesis is that the precipitous drop in the secondary market prices of securitizations during the crisis reflected bad news about fundamental values. Most narratives of the bust go beyond the frictionless null and emphasize mechanisms that amplified the reaction of prices to the bad fundamental news. While there is less consensus on the specific mechanisms that were at work, the two that have received the most attention in the theoretical literature are fire sales and buyers' strikes.

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[9] Beltratti and Stulz (2012), Fahlenbrach and Stulz (2011), and Erel, Nadauld, and Stulz (2013) argue that incentive conflicts between shareholders and managers have little power to explain the performance of banks during the crisis.

[10] The "too big to fail" version of this story focuses on the government's role as an implicit creditor of large financial institutions. Under this explanation, these institutions bought securitizations to rationally maximize the value of their implicit government guarantees. For instance, see Acharya, Cooley, Richardson, and Walter (2009), Acharya and Richardson (2009), Acharya, Schnabl, and Suarez (2013), and Iannotta and Pennacchi (2012).

[11] The literature on risk-taking incentives in insurance companies is less well developed than the comparable literature on mutual funds. Important exceptions include Becker and Ivashina (2014), who show that within rating insurers tend to hold riskier corporate bonds, and Koijen and Yogo (2013), who study regulatory capital arbitrage by insurers.

B.1 Fire sales

In fire sales-based explanations, binding leverage constraints forced financial intermediaries—who were the natural holders of securitizations and had the highest valuations—to sell to other investors with lower valuations. The resulting decline in prices further tightened leverage constraints, leading to further forced sales. Thus, fire sales are a natural amplification mechanism whereby some initial moderately bad news could have ultimately had a severe impact on prices. A critical feature of these explanations is that the decline in the prices of securitizations was associated with increased trading activity: the identity of the marginal investor changed because natural holders were forced to sell their holdings to others.[12]

B.2 Buyers' strikes

In "buyers' strike" explanations for the collapse of nontraditional securitization markets, uncertainty about the ultimate value of securitizations rose dramatically, causing prices to enter a downward spiral characterized by a near absence of trade. Precipitous price declines and a collapse of trading volume may be explained by a variety of frictional amplification mechanisms. In Diamond and Rajan (2012), for instance, institutions that would have otherwise sold assets at fire-sale prices instead refused to do so due to a risk-shifting problem. By contrast, Dang, Gorton, and Holmstrom (2013) and Hanson and Sunderam (2013) rely on adverse selection mechanisms. In these models, bad news lowered prices and raised uncertainty about asset valuations; as a result, the scope for adverse selection between informed and uninformed investors became too large, and trade collapsed. Milbradt (2012) presents a model where trade froze because financial intermediaries wished to avoid recognizing losses that would tighten their capital constraints. In his model, prices fall until the potential profits from transacting exceed the shadow cost of the tightening capital constraints.

Thus, different explanations for the bust have very different implications for aggregate trading patterns. The fundamentals-driven narrative suggests no reason for trading behavior to change with the onset of the financial crisis, while the fire sales narrative suggests increased trade at the beginning of the crisis, and the buyers' strike narrative suggests a collapse of trade.

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[12] Merrill, Nadauld, Stulz, and Sherland (2014) provide evidence that some insurers sold some nonprime RMBS at fire sale discounts. However, the aggregate volume of transactions they study is quite small. Relatedly, Ellul, Jotikasthira, Lundblad, and Wang (2014) find that P&C insurers who were subject to mark-to-market accounting were more likely to sell downgraded securitizations than life insurers who were subject to historical cost accounting.

III. Data

A. Mutual fund and insurance holdings

Our primary data set is the Thomson Reuters eMAXX database of quarterly security-level holdings of asset-backed securities by U.S.-domiciled mutual funds and insurance companies. Thomson Reuters obtains par value holdings data from regulatory filings—Schedule D for insurance companies and Forms N-CSR(S) and N-Q for mutual funds—as well as directly from these investors. Our sample period runs from 2003Q1–2010Q4, which is long enough to allow us to study changes in the demand for securitizations during the boom as well as during the crisis. Our sample of investor-quarter observations conditions on having at least one securitization in the portfolio, including GSE MBS. Thus, the investors that are missing from the sample are those that by regulation or by choice never hold securitizations.

Because the types of distortions in beliefs and incentives posited by the theoretical literature are likely to operate at relatively low frequencies, in most of our cross-sectional analyses we collapse our data to investor-year observations by taking an equal-weighted average within each year. Our analysis of trading behavior during the crisis uses quarterly data because annual data would fail to fully capture the dynamic response of trading to liquidity shocks.

B. Securities

We supplement our holdings data by collecting detailed security-level data from a number of sources. To differentiate between traditional and nontraditional securitizations, we collect comprehensive security data from the three major credit rating agencies—Fitch, Moody's, and S&P—and from Bloomberg. Using this data, we classify securitizations into the six broad collateral types discussed in Section I: (1) GSE MBS, (2) CMBS, (3) consumer ABS, (4) prime private-label RMBS, (5) nonprime private-label RMBS, and (6) CDOs. Our focus is on explaining the demand for the nontraditional securitizations that were at the heart of the credit boom and crisis. We therefore calculate the *nontraditional share*, the share of nonprime RMBS and CDOs in a given investor's overall bond portfolio. In addition, we collect data on the security's coupon or spread at issuance from Moody's and Bloomberg, the initial credit rating from Fitch, Moody's and S&P, and the time series of outstanding amounts from Bloomberg.

C. Mutual funds

We also collect data on the characteristics of the investors in our eMAXX data. We obtain mutual fund investment objectives, net assets, returns, and flows from the CRSP Mutual Fund Database.[13] Our cross-sectional analyses focus on bond and hybrid mutual funds, excluding index funds, equity funds, government bond funds, money market funds, and municipal bond funds. We obtain biographic data on the portfolio managers of mutual funds from Morningstar, including their start and end dates managing different funds. We measure each manager's experience as the number of years since the first time we observe them managing a mutual fund in the Morningstar data.

D. Insurance companies

We obtain insurance company data from AM Best, including information on insurers' assets, capitalization, and AM Best's financial strength rating for individual insurers.[14] Overall, our data on insurance companies is similar to our data on mutual funds, except that we do not have biographic data on insurer portfolio managers.

E. Summary statistics and aggregate holdings

Table 1 provides summary statistics for our main data on mutual funds and insurers. Panel A covers mutual funds and the unit of observation is a fund-year. The median fund has net assets of $256 million and total par bond holdings of $195 million. It is managed by two portfolio managers who average roughly eight years of experience between them. The median fund in our data invested about 1% of its bond portfolio in nontraditional securitizations. Highlighting the importance of cross-sectional heterogeneity, the distribution of nontraditional share is highly right-skewed with an average of 4%.

Panel B of Table 1 reports summary statistics for insurance companies. Because most insurance groups centrally manage the investment portfolios of their subsidiaries, we calculate summary statistics and perform our analyses at the insurance group level. Specifically, we use organizational hierarchy information from AM Best to aggregate holdings and firm characteristics up

[13] To do so, we construct a fund-level link between eMAXX and CRSP. We are able to link 84% (2,355 out of 2,813) of mutual funds in eMAXX to CRSP.

[14] We are able to match 84% (3,630 out of 4,302) of insurance companies in eMAXX to AM Best. We drop insurer separate accounts, which appear in eMAXX in some years but not others, from our baseline sample.

to the group level. The size distribution of insurance firms is highly right-skewed with the mean and median firms having $5,652 and $153 million in assets. The mean group had 2% of its aggregate bond portfolio invested in nontraditional securitizations.

Combining our eMAXX holdings data with data from the Flow of Funds and SIFMA, Table 2 reports the fractions of different categories of private credit securities held by insurers and mutual funds. Panel A reports holdings of all private credit securities, which include corporate bonds, foreign bonds, and privately issued ABS. In 2003Q2, insurers owned 26% of private credit securities. This share trended down to 20% by 2010Q4. At the same time, mutual funds' share of private credit securities trended up from 7% in 2003Q2 to 11% in 2010Q4. Thus, our data capture two of the largest investors in credit assets. We use these numbers as a benchmark for assessing the overall weight of insurers and mutual funds within private credit securities markets.

We next report holdings of traditional consumer ABS and CMBS. Both insurers and mutual funds were underweight traditional consumer ABS. However, insurers were overweight CMBS, holding approximately one-third of outstanding CMBS from 2003–2010. This is consistent with insurers' long-standing expertise in commercial real estate. According to the Flow of Funds, insurers' market share of all commercial mortgages, not including CMBS, averaged 28% from 1952–2000.

Panel B of Table 2 shows the evolution of outstanding amounts and holdings of private-label RMBS and CDOs. This panel shows that outstanding RMBS and CDOs grew rapidly during the boom. Although both insurers and mutual funds increased the fraction of their portfolios invested in these securities, they did not keep up with the overall market and became more underweight as issuance boomed. For example, while the share of nonprime RMBS in the overall market for private credit securities grew from 8% in 2003Q2 to 17% in 2007Q2, nonprime RMBS rose from only 4.2% to 5.4% over this period as a share of insurance companies' portfolios. We see similar patterns for mutual funds. These results apply across the capital structures of securitizations: in untabulated results, we find that insurance companies and mutual funds were not tilting their portfolios towards tranches with a particular rating. Approximately 80% of their holdings were rated AAA, which is roughly the share of issuance volume that was AAA-rated.

Overall, the aggregate evidence suggests that demand for nontraditional securitizations did not primarily come from the mutual funds and insurers.[15] Though these investors do not seem to have driven the overall growth of nontraditional securitization, they were still important holders of these products, with about $157 billion in total holdings as of 2007Q2. In the next section, we undertake a detailed analysis of the cross-sectional determinants of insurance company and mutual fund holdings. To the extent that these investors were affected by the same distorted incentives and beliefs as other investors, the cross-sectional patterns in their holdings should shed light on drivers of the boom in nontraditional securitization more generally.

IV. The Boom

In this section, we use our data to explore the forces that shaped investor demand during the 2003–2007 securitization boom. As discussed in Section II, the two main explanations we explore are those emphasizing distorted incentives and those highlighting distorted beliefs.

A. The importance of investor heterogeneity

The market for private securitizations grew explosively between 2003 and 2007. Figure 1(a) shows the dramatic growth of private securitizations, which was concentrated in nontraditional securitizations. Issuance of nontraditional securitizations almost quadrupled from $98 billion in 2002Q4 to $420 billion at the peak in 2006Q4. By comparison, issuance of traditional securitizations roughly doubled from $103 billion in 2002Q4 to $200 billion at its peak in 2007Q2.

As this surge in issuance was taking place, there was surprisingly little adjustment in the prices of securitizations. Figure 1(b) plots the quarterly time series of average credit spreads for AAA-rated securitizations backed by different types of collateral from 2003Q1–2007Q4. We compute value-weighted averages of new-issue spreads, restricting attention to the spreads on floating rate notes indexed to one-, three-, and six-month LIBOR to avoid benchmarking issues.

During the boom, credit spreads on AAA-rated nontraditional securitizations were significantly wider than those on other AAA-rated assets, including traditional securitizations and corporate bonds. The difference in spreads between traditional and nontraditional AAA-rated bonds,

[15] The National Association of Insurance Commissioners also finds that insurer holdings of CDOs were quite low. See http://www.naic.org/capital_markets_archive/110218.htm.

while moderate in absolute terms, was economically meaningful relative to typical credit spreads. Indeed, spreads on AAA-rated nonprime RMBS and CDOs were closer to those on BBB-rated corporate bonds than to those on AAA-rated corporate bonds. During the height of the boom from 2004Q1–2007Q2, AAA-rated spreads averaged 9 basis points (bps) for consumer ABS, 22 bps for nonprime RMBS, and 34 bps for CDOs. This can be compared with corporate bond spreads that averaged 4 bps for AAA-rated bonds and 37 bps for BBB-rated bonds.[16]

At the same time, we find little cross-sectional dispersion of spreads within a given rating and collateral class. For instance, from 2004Q1–2007Q2 the cross-sectional standard deviation of spreads among AAA-rated consumer ABS averaged 10 bps, whereas the cross-sectional dispersion for AAA-rated CDOs averaged 12 bps. Thus, the bulk of variation in credit spreads within a given rating was *across* collateral classes as opposed to *within* collateral class.[17]

The wide spreads on nontraditional securitizations are an underappreciated fact about the boom. Conventional descriptions of the boom often neglect heterogeneity across investors and across securities, implicitly assuming that all investors treated all AAA-rated securitizations as nearly riskless. However, the price variation we observe suggests that investor heterogeneity was important. While some buyers may have treated all AAA-rate securitizations the same, they were infra-marginal. Indeed, the marginal investor appears to have differentiated between the risks of traditional and nontraditional securitizations. Of course, this fact does *not* imply that investors got prices “right” during the boom. Given the size and systematic character of the ex-post losses, spreads should presumably have been an order of magnitude larger. However, the wider spreads on nontraditional securitizations suggest that some investors understood the ordinal ranking of risk across products.

Our investor-year panel of holdings underscores the importance of investor heterogeneity in their attitudes towards nontraditional securitizations. Table 3 reports a simple variance decomposition. Panel A shows the fraction of variation in nontraditional share among mutual funds that can be explained by different fixed effects. Most variation in investors’ portfolio allocations to nontraditional securitizations was variation across investors, as opposed to common variation over

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[16] Merrill, Nadauld, and Strahan (2014) also find that spreads on private securitizations were wider than those on comparably–rated corporate bonds during the 2003–2007 boom.

[17] Thus, our results do not contradict those in Adelino (2010), who finds that, in the cross-section of AAA-rated subprime RMBS, new-issue credit spreads have very little predictive power for future downgrades or default.

time. Specifically, time fixed effects can explain less than 2% of total variation in the portfolio share of nontraditional securitizations. Investment-objective fixed effects or objective-by-time effects can explain less than 20% of total variation. Fund fixed effects, on the other hand, explain more than 60% of total variation. The remaining columns show that some of the fund-level variation can be explained by similarities among different funds in the same family. However, in large families with at least 10 funds, there was significant within-family variation, suggesting that heterogeneity across individual portfolio mandates and managers played an important role.

Panel B of Table 3 performs a similar exercise for insurers. As with mutual funds, variation across insurers was crucial, and common variation over time can explain less than 1% of total variation in the portfolio share of nontraditional securitizations. We perform the variance decomposition analysis using firm instead of group-level data to show that there was relatively little within-group variation: group fixed effects capture almost as much cross-sectional variation (47%) in nontraditional share as do firm fixed effects (58%). This means that we are unlikely to lose much interesting variation when conducting portfolio holdings analysis using group-level data.

The variation in securitization prices across collateral types and the variation in portfolio shares across investors both suggest that there was important heterogeneity in investor attitudes towards securitizations. To better understand the factors that drove investor demand, we now examine the cross-sectional variation in our holdings data.

B. What explains mutual funds' securitization holdings?

We first examine the cross-sectional determinants of mutual fund holdings of nontraditional securitizations. In Table 4 we estimate cross-sectional regressions relating *nontraditional share*, the portfolio weight in nontraditional securitizations, to a variety of fund and manager characteristics. We estimate separate regressions for each year from 2004–2009. The regressions include investment objective fixed effects to isolate variation across funds with the same investment objective.

The strongest and most consistently significant driver of mutual fund holdings of nontraditional securitizations appears to have been portfolio manager experience, measured as the number of years each manager has been managing mutual funds. Using the start dates for fund-manager pairs in our Morningstar data, we calculate the first time each manager appears. We then compute the manager's experience as the difference between December 31, 2004 and this date. For team-managed funds, we take the average level of experience across individual managers. We label managers as experienced if they were above the median level of experience on December 31, 2004.[18]

Except for 2009, where it is near zero, the coefficient on experience is negative and statistically significant. The coefficient is largest in magnitude in 2007, when the nontraditional share of experienced managers was 3.3% less than the nontraditional share of inexperienced managers. This effect is economically large compared to the average nontraditional share of 4.5%.

Figure 2(a) depicts this finding graphically, plotting the average nontraditional share of funds managed by experienced versus inexperienced managers. Both experienced and inexperienced funds started with about a 3% portfolio weight in nontraditional securitizations. Starting in 2004, all managers increased their nontraditional share, but inexperienced managers increased their nontraditional share by far more than experienced managers. The nontraditional share of inexperienced managers peaked at 8% while that of experienced managers peaked at 5%.[19]

The distribution of mutual fund right-size is skewed, with the 250 largest funds, or about one third of our sample, accounting for about 90% of aggregate bond holdings. To make sure that our results are not driven by many small funds, in Panel B of Table 4 we estimate our regressions for the subsample of the 250 largest funds. We obtain very similar results for the subsample of large funds.

B.1 What drives the effect of manager inexperience?

One interpretation of the important role of manager experience is that it reflects incentive problems. For instance, Chevalier and Ellison (1997) argue that the shape of the relationship between fund flows and past performance determines the risk-taking incentives facing the fund and show that performance-flow is stronger in younger funds.[20]

However, Table 5 suggests that inexperienced bond mutual fund managers did not face stronger or more convex performance-flow relationships. We estimate monthly regressions of fund flows (scaled by lagged assets) on lagged fund returns and their interaction with a manager's experience. To capture the dynamics of investor learning about manager skill, in these performance-

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[18] By measuring experience as of 2004, we reduce concerns that funds wishing to invest in securitizations endogenously chose the younger managers in response to the boom.

[19] It is also possible to measure manager age using our Morningstar data. In untabulated results, we find that it is experience and not age that matters. Although younger managers tend to have higher nontraditional shares, especially around the peak of the credit boom, the difference is much smaller at around 1%.

[20] Chevalier and Ellison (1999) argue that because younger managers are more likely to be terminated for bad performance, they in fact face a more concave payoff function and therefore should take less risk.

flow regressions we update a manager's experience each month, and consider a manager to be experienced if she is above the median of the experience distribution at that time. Consistent with the prior literature, we find that fund flows respond strongly to past performance. However, when we interact past performance with experience, we do not find a stronger performance-flow relationship for inexperienced managers. If anything, performance-flow sensitivity appears to be slightly stronger for experienced managers, although the economic magnitude of this effect is small. Figure 2(b) depicts these results graphically.[21]

If not differences in incentives, what explained the strong tendency of inexperienced managers to invest in nontraditional securitizations? It could be that past experiences have a strong effect on managers' beliefs as in theories of reinforcement learning. This idea is explored by Greenwood and Nagel (2009), Malmandier and Nagel (2011, 2014), and Campbell, Ramadorai, and Ranish (2013). For example, Greenwood and Nagel (2009) find that young managers were more heavily invested in technology stocks at the peak of the technology bubble. In the context of bond markets, managers who have not managed through a credit cycle or experienced sharp movements in interest rates might be less likely to fully appreciate the tail risk exposure of securitizations.

In Table 6, we find evidence consistent with this reinforcement learning view. In Panel A, each column defines the experienced dummy as a different cutoff for the first year that the manager started to manage mutual funds. The effect of experience seems to be highly nonlinear—in our data it appears to matter most when a manager has at least seven to eight years of experience. These are the managers who were active during the dislocations of fall 1998, which saw turbulent fluctuations in credit spreads following Russia's default and perhaps learned about tail risk from that episode.

In Panel B, we restrict attention to the subset of experienced managers who managed any fund, not necessarily the one in question, during 1998. The regressions in Panel B show two interesting results. First, managers whose funds suffered poor returns or heavy outflows in 1998 steered clear of nontraditional securitizations in 2007.[22] Second, the subsequent effect of a bad 1998

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[21] We have also examined fund tracking error and do not find any evidence that inexperienced managers have larger tracking error. Thus, the higher nontraditional share of inexperienced managers does not appear to be part of a broader pattern of deliberate risk taking which would be reflected in a larger tracking error.

[22] To capture managers' firsthand experience of bad outcomes, we take the minimum returns or flows across all funds managed by a given manager in 1998. For team-managed funds, we then take the minimum across individual managers.

outcome is weaker for managers who had already accumulated significant experience by 1998.[23] Focusing on column (1), less experienced managers whose funds had performed well in 1998 allocated 6% more of their portfolios to nontraditional securitizations in 2007 than other managers.

The reinforcement learning story also suggests that experience may affect the way managers reacted to the surge in house prices during the boom. Specifically, more experienced managers may have been less influenced by positive recent house price appreciation than less experienced managers. Table 7 offers some suggestive evidence of this. We regress the nontraditional share in 2007 on the lagged change in house prices in the MSA where the fund manager was located. The coefficient on local house price appreciation is statistically and economically significant. A one-standard-deviation change in annualized house price appreciation over the 2003–2006 period is associated with a 1.2% higher nontraditional share, suggesting that local real estate conditions may have affected managers' attitudes towards nontraditional securitizations. In column 4, we control for the interaction of local price appreciation and manager experience. Although the interaction term is not statistically significant, the pattern of coefficients is suggestive. The interaction between experience and house price appreciation offsets more than half of the direct effect of house price appreciation.

In summary, our evidence suggests a role for reinforcement learning, whereby investors are more likely to understand certain risks only once they have personally experienced bad outcomes. This adds a dynamic component to recent narratives suggesting that investors bought securitizations because they neglected tail risks (Gennaioli, Shleifer, and Vishny [2012]). Specifically, risks that investors have not experienced for many years would be more likely to be neglected than risks that investors have recently experienced. In other words, the process of "collective forgetting" that contributes to booms and busts may be path dependent.

B.2 Isolating the effects of performance flow

While differences in incentives generated by performance flow do not appear to be driving our results on manager experience, they could still be an important determinant of mutual fund investments in nontraditional securitizations. The ideal experiment to isolate the effect of incentives

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[23] It is also possible that the crisis was a period during which investors learned a lot about the ability of fund managers active at the time, explaining the importance of being active during 1998. However, it does not explain why managers who performed worse in 1998 would hold fewer nontraditional securitizations.

would hold fixed fund managers' information and investment opportunity set while varying their risk-taking incentives. This suggests comparing the investment decisions one manager makes for two funds with the same investment objective but different performance-flow sensitivities.[24]

Variable annuities provide a laboratory to approximate this ideal experiment. Variable annuities are an insurance contract whose value depends on the performance of the investment selected by the owner of the insurance contract. The underlying investment options are typically mutual funds. Variable annuity funds are regulated and structured just like regular mutual funds under the Investment Company Act of 1940. Indeed, for many variable annuity funds, there is also a regular mutual fund with the same manager and mandate. For example, Hartford High Yield HLS Fund is a variable annuity fund in our data, and the Hartford High Yield Fund is the corresponding regular mutual fund. The two funds have the same investment goal and investment strategy and are managed by the same team of three portfolio managers. The only difference between the two is that the variable annuity fund serves as an "underlying investment option[s] for certain variable annuity and variable life insurance separate accounts of Hartford Life Insurance Company and its affiliates."

Because they are sold as a part of an insurance product, variable annuity funds are likely to face weaker performance-flow relationships than regular mutual funds. Table 8 shows this is the case. CRSP has little coverage of variable annuities prior to 2008Q3. As a result, we can only look at the performance-flow relationship after the crisis. Specifically, we use monthly data for the January 2009 to June 2013 period. We include all bond and hybrid funds and do not limit the sample to funds in our eMAXX data. Comparing the coefficients on past returns interacted with fund-type dummies, the performance-flow relationship for regular mutual funds is about twice as strong as that for variable annuity funds. The performance-flow relationship is depicted graphically in Figure 3(a).

Given such a large difference in the performance-flow relationship, the incentives story would predict that regular funds would engage in more risk taking than comparable variable annuity funds. To study the effects of these differences in performance flow on nontraditional share, we construct a sample of fund pairs with the same investment objective where one fund is a variable annuity fund, and its paired fund is a regular mutual fund managed by the same portfolio manager. We start with a

[24] In untabulated results, we find no effect of the estimated performance-flow sensitivity in simple direct tests. Specifically, funds that faced stronger performance-flow relationships did not have higher nontraditional shares.

sample of 328 variable annuity funds in our eMAXX data as of 2003Q4. We then manually search for a regular mutual fund that is offered by the same fund adviser.

We are able to find matching funds for 158 variable annuity funds. Figure 3(b) shows the time series of nontraditional share for matched pairs. Nontraditional shares track each other quite closely. Figure 3(b) does not control for differences in size that could, in principle, affect nontraditional share. However, controlling for size does not affect our results. Despite significant differences in the performance-flow relationship, Figure 3(b) shows that managers made similar investment decisions in their regular and variable annuity funds, suggesting that, for these managers, investments in nontraditional securitizations were not driven by the incentives they faced.

Overall, our analysis of mutual fund holdings suggests that beliefs played an important role determining holdings of nontraditional securitizations. Of course, these results do not rule out incentives-based explanations for the pre-crisis run-up in investor demand for nontraditional securitizations. Mutual funds may not have faced the relevant kinds of incentive distortions. Therefore, we next turn to our data on insurance company holdings.

C. What explains insurers' securitization holdings?

Insurance companies are the single largest institutional holder of credit securities. Moreover, since they are heavily regulated financial intermediaries, their holdings may give us insight into the incentive problems generated by such regulation.[25]

Following the same approach as in Table 4, Table 9 examines the cross-sectional determinants of insurers' nontraditional share over time. Three main facts emerge from the table. First, life insurers tended to hold more nontraditional securitizations than property and casualty (P&C) insurers. This may reflect the fact that payouts on life insurance policies are more predictable than payouts on P&C policies. Thus, life insurers effectively have a more stable funding base than P&C insurers, enabling them to take more risk as in Hanson, Shleifer, Stein, and Vishny (2014).

Second, larger insurers tended to hold more nontraditional securitizations than did smaller

[25] The experience of insurance company portfolio managers could have also played a role in driving their holdings of nontraditional securitizations. In untabulated results, we find some suggestive evidence consistent with this: public insurance companies that experienced worse stock returns during the 1998 crisis invested less in nontraditional securitizations in the mid-2000s. However, because our data on insurers lacks detailed biographical information on portfolio managers, we cannot perform the same detailed analysis for insurers that we do for mutual funds.

insurers. A one-standard-deviation increase in size was associated with a 0.9% higher nontraditional share, or about half of the average share of 2%. This may reflect the fact that there are fixed costs involved in investing in securitizations because it requires trading expertise and analytical infrastructure that is quite different from that required for corporate bonds. Larger insurers have larger portfolios over which they can amortize these fixed costs.[26]

The third main fact is consistent with the idea that investing in securitizations requires specialized knowledge and infrastructure: insurers with portfolios run by external managers held more nontraditional securitizations. This may reflect the fact that insurers could economize on their investing infrastructure by outsourcing part of their portfolio management to external managers. But it may also reflect an incentive conflict: if insurers could not perfectly risk-adjust performance, external managers may have been able to increase their compensation by taking excessive risks. Since they perform well in most states of the world, nontraditional securitizations may have been a particularly good avenue for such risk taking.

The insurance industry is even more concentrated than the mutual fund industry. In our data, the top 100 insurers held approximately 90% of total assets. (The cutoff for inclusion in the top 100 insurers has been stable over time at around $8 billion in total assets.) Since these large insurers likely had the scale necessary to invest in securitizations internally, it may be the case that there were different determinants of holdings of nontraditional securitizations among large insurers than among small insurers. To assess this possibility, Panel B of Table 9 replicates Panel A, restricting the sample to the top 100 insurers by size. Two main differences stand out. First, large insurers that used external managers did not hold more nontraditional securitizations than those using internal managers. This is consistent with the idea that larger insurers had the expertise necessary to effectively monitor their external managers and prevent excessive risk taking.

Second, among large insurers, those with lower capitalization levels invested significantly more in nontraditional securitizations. We hold the definition of capitalization constant over time to ensure that the results are not driven by shifts in the set of insurers that have low capital ratios. The economic magnitude is meaningful. A one-standard deviation increase in capitalization was

[26] An alternative explanation is that the effect of size reflects a too-big-too-fail problem. Large insurers may have held nontraditional securitizations because they expected government bailouts. However, the number of insurers large enough to expect such treatment is likely too small to drive our regression results.

associated with a 1.7% decrease in nontraditional share, relative to a mean share of 3.8%.

These results are consistent with the idea that risk-shifting was an important driver of nontraditional securitization holdings among large insurers. Equity holders are residual claimants on the value of an insurer's asset portfolio net of policyholder claims. An insurer's capitalization level may reflect the strength of the agency conflict between its equity holders and its creditors, including state guarantee funds. To combat this problem, regulators require insurance companies to maintain minimum levels of capital on a risk-adjusted basis. However, to the extent that these regulations are imperfect, poorly-capitalized insurers could have had stronger risk-shifting incentives and therefore have been more likely to hold nontraditional securitizations.

Table 9 lends support to the idea that incentive problems played a role in driving insurer demand for nontraditional securitizations. Heterogeneity among insurers is important: different incentive problems appear to matter for different insurers. Among smaller insurers, the key principal-agent relationship was between the insurer, which may have lacked the expertise necessary to directly invest in securitizations, and external portfolio managers. Among larger insurers, the key principal-agent relationship appears to have been between debt and equity holders.

In summary, our evidence suggests that both distorted beliefs and distorted incentives are likely part of the explanation for the pre-crisis surge in demand for nontraditional securitizations. Heterogeneity across investors is important: beliefs appear to have played an important role among mutual funds, while incentives appear to have played an important role among insurance companies.

V. The Bust

How did investor demand react once the financial crisis arrived in mid-2007? Did investors holding nontraditional securitizations hold onto them or sell them? And did investors with limited exposure to nontraditional securitizations step in as liquidity providers or stay on the sidelines? To answer these questions, we turn to the collapse of the market for securitizations from 2007–2009.

A. Aggregate trading patterns

As discussed in Section II, different explanations for the bust have different implications for aggregate trading patterns. The fundamentals-driven narrative suggests little reason for trading behavior to change with the onset of the financial crisis. In contrast, the conventional fire-sales narrative suggests increased trade at the beginning of the crisis, while the buyers' strike narrative suggests a collapse in trading volume.

In Figure 4, we begin by analyzing the time series of aggregate transactions by insurance companies. The figure shows the time series of aggregate insurer transactions by collateral type. We plot turnover, defined as the total par value of transactions (the sum of buys and sells) normalized by total average par holdings. Thus, if insurers sold all of their subprime RMBS holdings and bought subprime RMBS with the same par value, subprime RMBS turnover would be 200%. We take a four-quarter moving average to smooth the resulting series. As reference points, we also plot turnover for GSE MBS, which are relatively liquid, and corporate bonds, which are relatively illiquid.

Figure 4 shows that, during the boom, insurers traded nontraditional securitizations less frequently than GSE MBS but more frequently than corporate bonds. Pre-crisis turnover in nonprime RMBS and traditional consumer ABS was close to turnover in GSE MBS, while CMBS and CDOs traded far less frequently. As the crisis set in during mid-2007 and early 2008, trade in all types of private securitizations fell substantially. In contrast, turnover of GSE MBS and corporate bonds remained relatively stable throughout the crisis.

In untabulated results, we find similar aggregate trading patterns for mutual funds. We focus on insurers because eMAXX provides data on actual insurer transactions. For mutual funds, we do not directly observe transactions and must impute transactions from changes in holdings, adjusted for the change in each security's amount outstanding due to defaults and prepayments.[27] The results for mutual funds are similar to those for insurance companies. Turnover in nonprime RMBS fell from 27% in 2007Q2 to 14% in 2008Q4. Turnover in CMBS and CDOs was relatively stable before the start of the crisis in 2007Q3 and experienced large declines during the crisis. Finally, turnover of GSE MBS picked up during the crisis.

Overall, the aggregate trading patterns in our data seem more consistent with the buyers' strike than with the fire-sales narrative of the fall of nontraditional securitization. Trading volume plummeted at the same time that prices collapsed. In contrast, simple versions of the fire-sales story suggest that outsized declines in prices were mediated by high volumes of secondary market trade.

One major caveat to this interpretation is that we do not observe the full universe of

[27] While the overall par dollars of nontraditional securitizations held by mutual fund and insurers fell during the crisis, this primarily reflected prepayments and defaults as opposed to trade. When the collateral in a securitization prepays or defaults, the par holdings of all investors in the securitization decline. We use security-level data from Bloomberg on par outstandings to verify that the decline in holdings was driven by default and prepayments. Specifically, insurers and mutual funds held a constant fraction of the amount outstanding, but the total outstanding declined.

securitization holders or transactions: we only observe trades where at least one party was an insurer or mutual fund. However, as noted above, insurers and mutual funds hold a large fraction of total credit assets. To the extent that fire sales resulted in the aggregate transfer of security holdings from highly-levered intermediaries such as hedge funds and broker-dealers to the broad class of investors who operate with lower leverage, such as mutual funds and insurers, our data should capture at least one side of the transaction. Nonetheless, it remains possible that there were widespread fire sales which led to a significant reallocation of securitization holdings amongst highly-levered intermediaries, but not between leveraged intermediaries and the investors our data cover.[28]

If mutual funds and insurers transacted little in nontraditional securitizations, how did they meet their liquidity needs during the crisis? To answer this question, we explore the cross-sectional variation in trading patterns. Specifically, we ask whether distressed mutual funds and insurers were more likely to sell nontraditional securitizations than others. Even though these investors sold little in the aggregate, cross-sectional results may help to shed light on how other investors might have traded in response to liquidity shocks during the crisis.

B. Cross-sectional trading patterns

We begin by analyzing the trading behavior of mutual funds. For mutual funds, we have a simple proxy for liquidity shocks: fund flows. In untabulated results, we find that mutual funds with higher nontraditional shares experienced larger outflows during the crisis. Investors started withdrawing from funds with high nontraditional shares during the second half of 2007, and by the height of the crisis in the second half of 2008, a one standard deviation change in nontraditional share (about 9%) was associated with about 6.3% larger (annualized) outflows.

How did mutual funds facing redemptions meet their liquidity needs during the crisis? Table 10 asks which types of securitizations funds bought and sold in response to inflows and outflows. We examine net purchases of consumer ABS, GSE MBS, CMBS, and nontraditional securitizations, each

[28] Amplification could also occur in a manner similar to the traditional fire-sale mechanism, but involving little secondary market trade. For instance, an initial decline in RMBS prices could have changed the marginal investor in RMBS from specialized trading desks or investment vehicles to corporate headquarters within a financial institution. If headquarters responded by imposing stricter capital requirements on RMBS positions, this may have led to a further decline in quoted prices, which may have led headquarters to impose even stricter requirements. The resulting spiral could have amplified the drop in prices even in the absence of secondary volume. Anecdotally, there were several large transactions involving the transfer of securitizations within the same conglomerate from structured investment vehicles and other specialized off-balance sheet vehicles to a firm's balance sheet during the crisis (e.g., Acharya, Schnabl, and Suarez [2013]).

scaled by the fund's lagged holdings of that securitization type. To ensure our results are not driven by outliers, we winsorize the dependent variable at the 5th and 95th percentiles.[29] As a reference point, if funds simply responded to inflows by proportionately expanding their portfolios, we would expect the coefficient on inflows to be one. Similarly, if funds responded to outflows through proportionate liquidation, the coefficient on outflows would be negative one.

Table 10 shows that mutual funds experiencing inflows increased their holdings of each securitization type roughly proportionately. GSE MBS holdings expand slightly more than one-for-one, while nontraditional securitization holdings expand less than one-for-one. However, mutual funds experiencing outflows concentrated their liquidations in GSE MBS. For all other securitization types, the coefficient on outflows is generally not statistically different from zero and is significantly different from the proportional liquidation benchmark of negative one. Moreover, as shown by the generally small and statistically insignificant interactions of inflows and outflows with the crisis dummy, funds' liquidity management practices were fairly similar in both the pre-crisis and crisis periods.[30] Thus, there is little evidence that mutual funds suffering outflows were forced to sell large volumes of nontraditional securitizations during the bust. Instead, distressed mutual funds appear to have been far more active sellers of GSE MBS.

We next turn to insurance company transactions in Table 11. As in our analysis of mutual funds, the dependent variables are net purchases of consumer ABS, GSE MBS, CMBS, and nontraditional securitizations, each scaled by the firm's lagged holdings of that securitization type and winsorized at the 5th and 95th percentiles. We use the percent change in the size of the insurer's overall fixed income portfolio as our proxy for liquidity shocks. This is similar to our use of fund flows in our analysis of mutual fund transactions.

Table 11 shows the types of securitizations insurers bought or sold when their overall portfolios grew or shrank. The results are qualitatively similar to the results of our mutual fund

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[29] We obtain qualitatively similar results if use median regressions, which are less influenced to outliers, or if we cap the dependent variable at 100%.

[30] The two exceptions are the coefficients on outflows interacted with crisis in the regressions of consumer ABS and GSE MBS that do not include objective-time fixed effects. Both suggest increased propensity to meet outflows during the crisis through sales of GSE MBS and consumer ABS. Figure 4 shows that turnover of consumer ABS recovered quickly after falling at the height of the crisis in late 2008.

analysis.[31] Insurers with growing portfolios tended to buy all types of securitizations, with GSE MBS showing the largest response. This pattern continued in the crisis, though insurers with growing portfolios stopped purchasing nontraditional securitizations. Insurers with shrinking portfolios tended to sell all types of securitizations, with GSE MBS showing the largest response and nontraditional securitizations showing the smallest response. These patterns continued in the crisis. There is little evidence that distressed insurers were forced to sell nontraditional securitizations during the bust. As with mutual funds, insurers appear to be much more active in transacting in more liquid markets.

Overall, these results point to the importance of liquidity management in a fire-sale context. Mutual funds and insurers that faced liquidity needs during the crisis largely transacted in the most liquid securitization market: the market for GSE MBS. This suggests that, if there were large volumes of forced sales at distressed prices in secondary securitization markets, they likely took place in the market for GSE MBS. Consistent with this interpretation, spreads on GSE MBS were very high in the fall of 2008, even after the government had explicitly guaranteed the GSEs. Indeed, some have argued that the first round of large-scale asset purchases by the Federal Reserve was particularly effective because it provided liquidity in the market for GSE MBS at a time when prices were distressed (see, for instance, Sack [2009] and Krishnamurthy and Vissing-Jorgensen [2013]).

VI. Conclusion

Nontraditional securitizations—nonprime RMBS and CDOs—were at the heart of the recent financial crisis. The demand for these securities helped feed the housing boom during the early and mid-2000s, while rapid declines in their prices during 2007 and 2008 generated large losses for financial intermediaries, ultimately imperiling their soundness and triggering a full-blown crisis. There are many anecdotal narratives and theoretical models of the rise and fall of demand for securitizations, but little systematic empirical evidence. Using micro-data on insurers' and mutual funds' holdings of both traditional and nontraditional securitizations, this paper begins to shed light on the economic forces that drove the demand for securitizations before and during the crisis.

[31] The coefficients in Table 11 are generally smaller in magnitude than the proportional benchmarks of one and negative one. This appears to reflect extreme outliers in the independent variable, overall portfolio growth. We recover coefficients closer to one when we exclude quarterly portfolio growth rates outside [-25%, 25%]. In addition, it could be the case that insurers transacted heavily in the Treasury market, which our data does not cover.

We document a number of robust stylized facts about the demand for nontraditional securitizations. First, heterogeneity across securitization types and investors is key to understanding the crisis. Beliefs appear to have been an important driver of mutual fund holdings of nontraditional securitizations. Although they did not face stronger performance-flow relationships, inexperienced mutual fund managers invested significantly more in these products than experienced managers. Consistent with the idea that beliefs—shaped by past firsthand experiences—played an important role, managers who had suffered through the market dislocations of 1998 invested substantially less in nontraditional securitizations than those who had not.

For insurance companies, incentives appear to have played an important role, though the nature of the relevant incentive conflict seems to have varied across small and larger insurance firms. Among small insurers, the key principal-agent relationship was between the insurer, which may have lacked the expertise necessary to directly invest in securitizations, and external portfolio managers. Among larger insurers, the key principal-agent relationship was between debt and equity holders. Overall, our evidence suggests that different motivations are important for understanding the holdings of different investor types.

While investor heterogeneity is important in the boom, the story of the bust is more uniform. In our data, the bust is characterized by a decline in aggregate trading volume for nontraditional securitizations. Consistent with the idea that adverse selection and other frictions contributed to a buyers' strike in these markets, prices fell significantly, even though very little trade took place. Insurers and mutual funds that needed liquidity transacted largely in the market for GSE MBS. Our results underscore the importance of optimal liquidity management in the context of fire sales.

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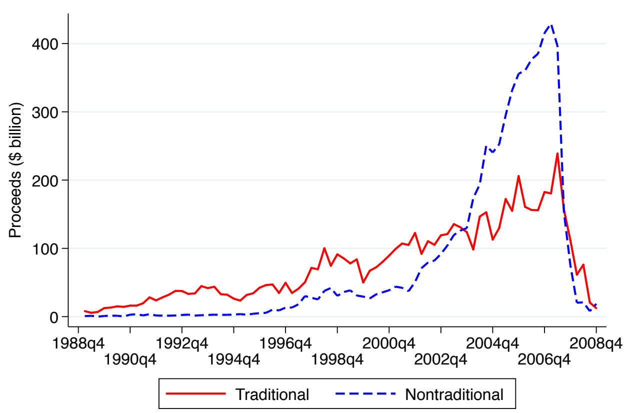
Figure 1
Issuance and Spreads on Traditional and Nontraditional Securitizations

This figure shows quarterly issuance and credit spreads on traditional and nontraditional securitizations. The underlying data is from SDC. Panel A plots quarterly issuance of traditional and nontraditional securitizations. Traditional securitizations include CMBS, prime RMBS, consumer ABS, and other ABS. Nontraditional securitizations include non-prime RMBS and CDOs. Panel B plots the credit spreads on newly issued AAA-rated securitizations versus the spreads on corporate bonds. Each quarter we compute the value-weighted average credit spread on securitizations, based on the underlying collateral. We compute this average for traditional consumer asset-backed securities backed by credit card loans, automotive loans, student loans, and other personal loans ("Consumer ABS"); private residential mortgage backed securities (RMBS) backed by subprime and Alt-A mortgages ("Non-Prime RMBS"); commercial mortgage backed securities (CMBS); and collateralized debt obligations ("CDOs"). To avoid benchmarking issues we restrict attention to the spreads on floating rate notes indexed to 1-, 3-, and 6-month LIBOR. For reference we plot the average secondary spreads over LIBOR (based on interest rate swaps) on 3-year AAA and BBB-rated corporate bonds from Barclays.

(a) Traditional vs. Nontraditional Issuance



(b) Credit Spreads on AAA-rated Tranches

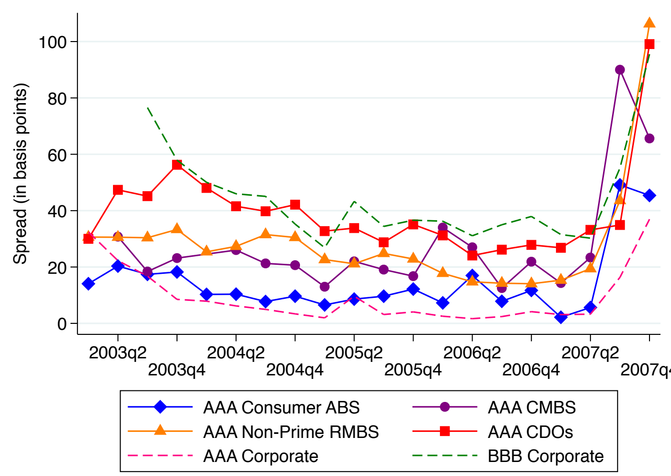


Figure 2
Mutual Fund Manager's Experience and Nontraditional Share

Panel A reports the average nontraditional share of mutual funds managed by experienced versus inexperienced portfolio managers. We split mutual funds into two groups based on the median value of the fund manager's experience. Manager experience is measured as of 2004Q4. For team-managed funds we take the average of individual managers. Panel B reports the strength of the performance-flow relationship in mutual funds managed by experienced versus inexperienced managers. Fund flows are winsorized at the first and ninety-ninth percentiles. We first adjust monthly fund returns and net flows for objective-month fixed effects. The figure then shows the mean of adjusted fund flows by decile of adjusted performance. Each month we define experienced funds are those with fund managers above the median of experience across all funds at that point time.

(a) Nontraditional Share

(b) Performance-Flow Relationship

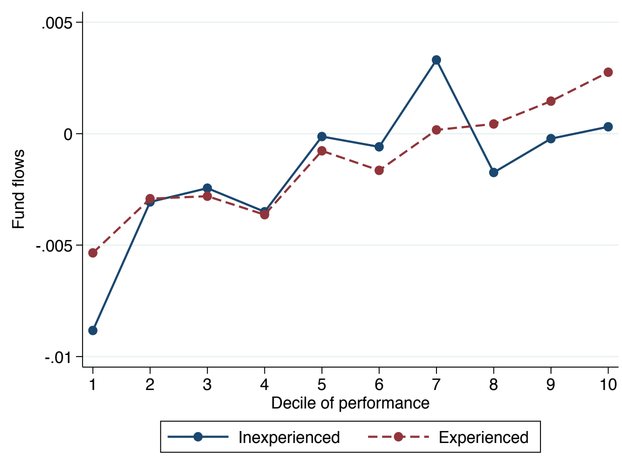
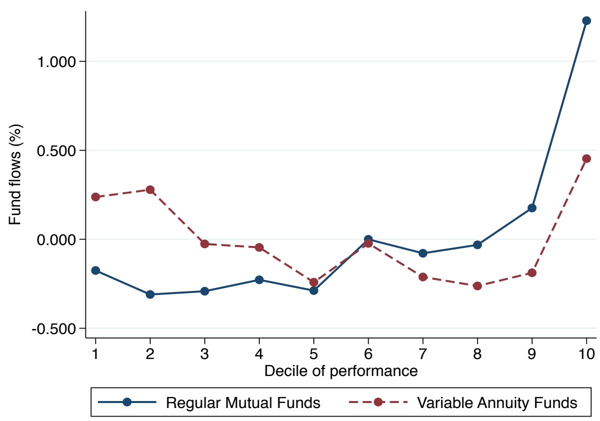


Figure 3
Variable Annuity versus Regular Mutual Funds

This figure reports the strength of the performance-flow relationship and holdings of non-traditional securitizations by variable annuity and regular mutual funds. Panel A reports the strength of the performance-flow relationship for variable annuity versus regular mutual funds. The sample consists of all bond and hybrid funds in CRSP Mutual Fund Database. The sample period is January 2009–June 2013. Fund flows are winsorized at the first and ninety-ninth percentiles. We first adjust monthly fund returns and net flows for objective-month fixed effects. The figure then shows the mean of adjusted fund flows by decile of adjusted performance. This adjustment is done separately for variable annuity and regular mutual funds. Panel B reports the nontraditional share of variable annuity and regular mutual funds. The sample consists of matched pairs of variable annuity and regular mutual funds that have the same investment objectives and are managed by the same portfolio managers. We form the sample of matched pairs as of 2003Q4.

(a) Performance-Flow Relationship



(b) Nontraditional Share

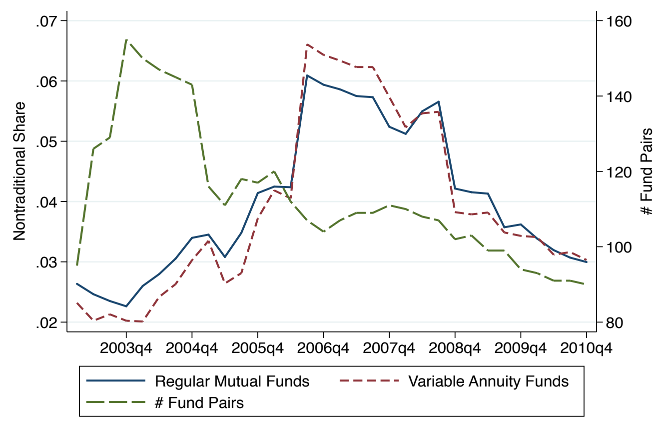


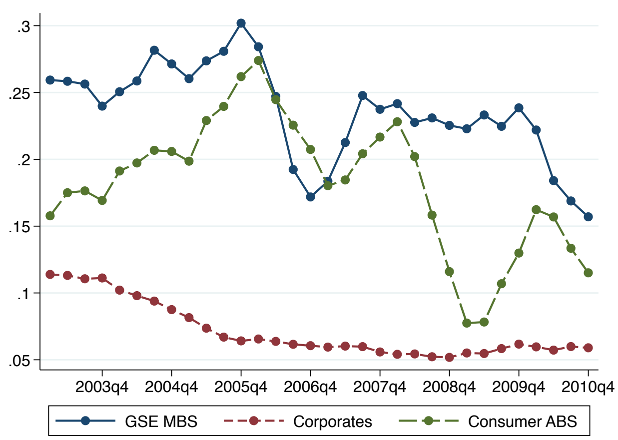
Figure 4
Insurance Company Portfolio Turnover

We aggregate all buy and sell transactions in a given collateral type across all insurance companies and scale it by the average value of aggregate holdings during quarters $t-1$ and t. In other words, aggregate turnover in collateral type c in quarter t is

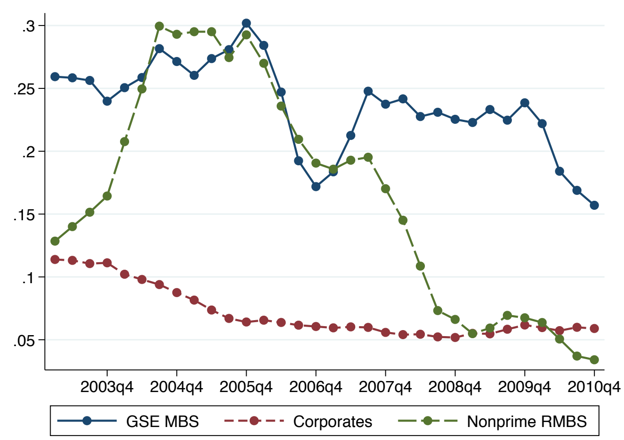
$$Turnover_{c,t} = \frac{Buy_{c,t} + Sell_{c,t}}{0.5 \cdot (Hold_{c,t} + Hold_{c,t-1})}$$

The figure plots the four-quarter moving average. For private securitizations and GSE MBS, we calculate aggregate transactions and holdings using eMAXX data. For corporate bonds, aggregate transactions are from Mergent FISD, while aggregate holdings are from the Federal Reserve's Flow of Funds Accounts.

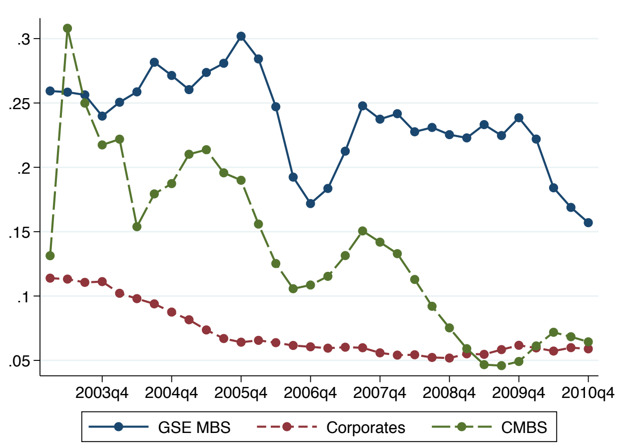
(a) Consumer ABS



(b) Nonprime RMBS



(c) CMBS



(d) CDO

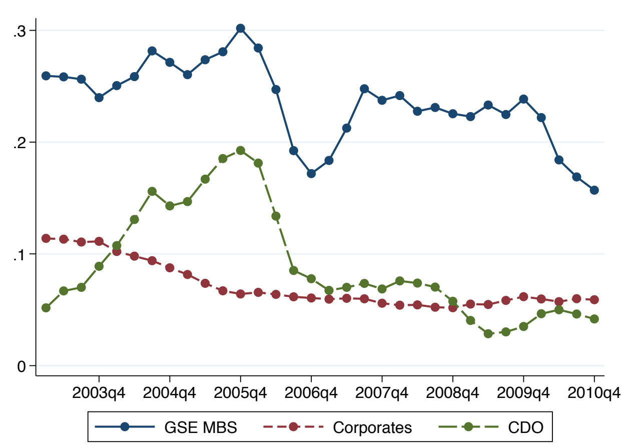


Table 1
Summary Statistics

This table reports summary statistics for mutual funds and insurance companies in our data. The sample of funds consists of bond and hybrid mutual funds. In Panel B, we aggregate data across all subsidiaries of each insurance group. Capitalization and strong rating are reported as of 2003.

	N	Mean	Median	SD	Min	Max
Panel A: Mutual Funds						
TNA (millions)	6,227	1,521	287	6,926	1	236,621
Bond holdings par (millions)	6,227	1,041	217	4,066	0	175,956
Family TNA (billions)	6,227	118.62	27.13	253.22	0.00	1,551.55
Team managed (dummy)	6,227	0.66	1.00	0.47	0.00	1.00
# fund managers	6,227	2.76	2.00	2.46	1.00	21.00
Experience (years)	6,227	8.49	7.87	4.51	0.00	29.06
ABS share (%)	6,227	2.98	0.52	6.05	0.00	79.10
Agency share (%)	6,227	24.49	17.12	25.96	0.00	100.00
CMBS share (%)	6,227	4.71	0.51	9.78	0.00	92.17
Nontraditional share (%)	6,227	4.50	0.91	8.90	0.00	100.00
Fund age (years)	6,227	15.96	13.63	11.95	0.15	83.80
Expense ratio (%)	6,227	0.89	0.85	0.40	0.00	3.74
Share of retail classes (%)	6,227	63.91	90.45	41.73	0.00	100.00
Family age (years)	6,227	41.53	33.79	25.01	0.54	86.14
Family equity share (%)	6,227	47.80	50.59	26.24	0.00	100.00
Family taxable share (%)	6,227	39.79	32.74	25.44	0.00	100.00
Family ETF share (%)	6,227	0.49	0.00	5.43	0.00	86.20
Family muni share (%)	6,227	8.30	7.02	8.78	0.00	97.63
Family retail share (%)	6,227	61.85	68.26	33.04	0.00	100.00
Panel B: Insurance Firms						
Assets	5,648	8,711	342	38,494	1	894,085
Nontraditional share (%)	5,648	2.17	0.48	4.32	0.00	71.89
Life	5,648	0.36	0.00	0.48	0.00	1.00
Capital/Assets	5,648	0.32	0.32	0.18	0.01	0.95
Strong rating	5,648	0.37	0.00	0.48	0.00	1.00
Mutual	5,648	0.27	0.00	0.45	0.00	1.00
External manager	5,648	0.72	1.00	0.42	0.00	1.00

Table 2
Outstanding Asset-Backed Securities and Holdings of Insurers and Mutual Funds by Underlying Collateral Type, 2003–2010

This table reports estimates of the outstanding balance of US asset-backed securities by underlying collateral type. The sources for estimated outstanding are listed in the footnotes. For each collateral type, we compute aggregate par holdings by insurers and mutual funds using our eMAXX holdings data. For the market, % refers to the share of a given collateral type in the aggregate outstanding amount of all private credit securities. For insurance and mutual funds, % refers to the shares of a given collateral type in the aggregate portfolios of insurance firms and mutual funds.

Panel A

	All private credit securities[a]						Traditional consumer ABS[b]						CMBS[c]					
	Market		Insurance		Mutual Funds		Market		Insurance		Mutual Funds		Market		Insurance		Mutual Funds	
	$	%	$	%	$	%	$	%	$	%	$	%	$	%	$	%	$	%
2003Q2	6,776	100.0%	1,755	25.9%	504	7.4%	701	10.3%	93	5.3%	22	4.4%	313	4.6%	108	6.1%	10	2.0%
2003Q4	7,178	100.0%	1,829	25.5%	531	7.4%	721	10.0%	100	5.5%	20	3.8%	343	4.8%	119	6.5%	11	2.0%
2004Q2	7,524	100.0%	1,927	25.6%	560	7.4%	726	9.7%	101	5.3%	25	4.4%	368	4.9%	130	6.7%	11	2.0%
2004Q4	8,071	100.0%	2,002	24.8%	594	7.4%	729	9.0%	98	4.9%	24	4.1%	394	4.9%	145	7.2%	13	2.1%
2005Q2	8,541	100.0%	2,060	24.1%	631	7.4%	762	8.9%	90	4.4%	24	3.8%	439	5.1%	153	7.4%	15	2.3%
2005Q4	8,852	100.0%	2,088	23.6%	660	7.5%	781	8.8%	89	4.3%	28	4.3%	506	5.7%	168	8.1%	21	3.2%
2006Q2	9,415	100.0%	2,127	22.6%	706	7.5%	794	8.4%	84	4.0%	23	3.3%	553	5.9%	185	8.7%	19	2.7%
2006Q4	10,103	100.0%	2,097	20.8%	764	7.6%	836	8.3%	76	3.6%	24	3.1%	614	6.1%	189	9.0%	24	3.2%
2007Q2	10,879	100.0%	2,132	19.6%	837	7.7%	870	8.0%	64	3.0%	27	3.2%	697	6.4%	195	9.1%	38	4.5%
2007Q4	11,577	100.0%	2,145	18.5%	886	7.7%	894	7.7%	68	3.2%	26	2.9%	758	6.5%	216	10.1%	41	4.6%
2008Q2	11,698	100.0%	2,143	18.3%	958	8.2%	894	7.6%	85	4.0%	34	3.6%	741	6.3%	222	10.4%	48	5.0%
2008Q4	11,170	100.0%	2,085	18.7%	956	8.6%	835	7.5%	75	3.6%	27	2.8%	718	6.4%	223	10.7%	50	5.3%
2009Q2	11,676	100.0%	2,146	18.4%	1,035	8.9%	808	6.9%	68	3.2%	26	2.5%	703	6.0%	221	10.3%	48	4.7%
2009Q4	11,654	100.0%	2,226	19.1%	1,121	9.6%	798	6.8%	70	3.1%	23	2.1%	671	5.8%	227	10.2%	52	4.6%
2010Q2	11,432	100.0%	2,288	20.0%	1,181	10.3%	744	6.5%	75	3.3%	32	2.7%	647	5.7%	220	9.6%	58	4.9%
2010Q4	11,816	100.0%	2,353	19.9%	1,243	10.5%	690	5.8%	68	2.9%	28	2.3%	617	5.2%	208	8.8%	59	4.8%

[a] Data on the outstanding quantity of all private credit securities, which include corporate bonds, foreign bonds, and privately issued ABS, is from table L.212 'Corporate and Foreign Bonds' of the Federal Reserve's Flow of Funds Accounts. Data on the holdings of insurers (which includes both P&C and life insurers) and mutual funds (which excludes money market mutual funds) is also from Table L.212.

[b] Data on the outstanding quantity of traditional consumer ABS, which consists of ABS collateralized by credit card debt, automotive loans, student loans, manufactured housing and equipment loans, is from SIFMA at http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/SF-US-ABS-SIFMA.xls.

[c] Data on the outstanding quantity of CMBS, which consists of MBS collateralized by commercial mortgages and multifamily residential mortgages, is from Table L.219 'Multifamily Residential Mortgages' and Table L.220 'Commercial Mortgages' of the Federal Reserve's Flow of Funds Accounts.

Table 2(continued)
Outstanding Asset-Backed Securities and Holdings
of Insurers and Mutual Funds by Underlying Collateral Type, 2003–2010

Panel B																		
	Prime RMBS[a]						Nonprime RMBS[b]						CDOs[c]					
	Market		Insurance		Mutual Funds		Market		Insurance		Mutual Funds		Market		Insurance		Mutual Funds	
	$	%	$	%	$	%	$	%	$	%	$	%	$	%	$	%	$	%
2003Q2	297	4.4%	29	1.6%	6	1.3%	563	8.3%	73	4.2%	8	1.6%	279	4.1%	21	1.2%	4	0.8%
2003Q4	276	3.8%	22	1.2%	5	0.9%	601	8.4%	56	3.1%	8	1.5%	302	4.2%	20	1.1%	5	0.9%
2004Q2	314	4.2%	29	1.5%	10	1.7%	765	10.2%	65	3.4%	10	1.8%	347	4.6%	21	1.1%	6	1.0%
2004Q4	351	4.3%	51	2.5%	10	1.7%	929	11.5%	83	4.2%	14	2.4%	391	4.8%	23	1.1%	5	0.9%
2005Q2	388	4.5%	55	2.7%	11	1.7%	1,139	13.3%	96	4.7%	16	2.5%	454	5.3%	21	1.0%	3	0.5%
2005Q4	425	4.8%	62	3.0%	13	2.0%	1,349	15.2%	109	5.2%	18	2.7%	517	5.8%	24	1.2%	2	0.4%
2006Q2	462	4.9%	69	3.2%	12	1.7%	1,579	16.8%	117	5.5%	14	2.0%	627	6.7%	24	1.1%	2	0.2%
2006Q4	499	4.9%	74	3.5%	15	1.9%	1,808	17.9%	122	5.8%	16	2.1%	795	7.9%	23	1.1%	2	0.2%
2007Q2	525	4.8%	73	3.4%	19	2.2%	1,852	17.0%	115	5.4%	19	2.3%	961	8.8%	21	1.0%	2	0.3%
2007Q4	552	4.8%	84	3.9%	25	2.8%	1,895	16.4%	130	6.1%	17	1.9%	1,005	8.7%	21	1.0%	2	0.3%
2008Q2	518	4.4%	83	3.9%	23	2.4%	1,729	14.8%	138	6.4%	18	1.9%	1,004	8.6%	27	1.3%	4	0.4%
2008Q4	484	4.3%	82	3.9%	22	2.3%	1,563	14.0%	136	6.5%	16	1.7%	1,018	9.1%	27	1.3%	2	0.2%
2009Q2	436	3.7%	74	3.4%	18	1.8%	1,437	12.3%	126	5.9%	13	1.3%	987	8.5%	26	1.2%	2	0.2%
2009Q4	389	3.3%	67	3.0%	16	1.5%	1,311	11.2%	125	5.6%	11	1.0%	936	8.0%	26	1.2%	1	0.1%
2010Q2	350	3.1%	62	2.7%	20	1.7%	1,221	10.7%	119	5.2%	13	1.1%	872	7.6%	25	1.1%	2	0.1%
2010Q4	311	2.6%	54	2.3%	22	1.8%	1,131	9.6%	107	4.6%	14	1.1%	838	7.1%	24	1.0%	2	0.1%

[a] Data on the outstanding quantity of prime RMBS is from SIFMA at
http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/sf-us-nonagency-outstanding-sifma.xls.

[b] Data on the outstanding quantity of nonprime RMBS, which includes subprime and Alt-A RMBS, is from SIFMA at
http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/sf-us-nonagency-outstanding-sifma.xls.

[c] Data on the outstanding quantity of CBOs, CDOs, and CLOs is from SIFMA at
http://www.sifma.org/uploadedFiles/Research/Statistics/StatisticsFiles/SF-Global-CDO-SIFMA.xls.
SIFMA provides data on global CBOs, CDOs, and CLOs outstandings. Based on SIFMA's issuance data by currency, we assume that 75% of outstanding CDOs and CLOs are USD-denominated.

Table 3
Nontraditional Share Variance Decomposition

This table reports the R^2 from the regressions of nontraditional share on various fixed effects. Panel A reports the results for bond and hybrid mutual funds in our data; Panel B reports the results for insurance firms. The sample period is 2003–2010.

Panel A: Mutual Funds

	Date	Objective	Objective × date	Fund	Fund family: All	Fund family with at least 5 funds	Fund family with at least 10 funds
Constant	0.045***	0.045***	0.045***	0.045***	0.045***	0.047***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.014	0.167	0.191	0.621	0.361	0.282	0.198
N	6,227	6,227	6,227	6,227	6,227	4,262	2,341

Panel B: Insurance Firms

	Date	Firm	Group
Constant	0020***	0020***	0020***
	(0000)	(0000)	(0000)
Adjusted R^2	0002	0665	0504
N	15,538	15,538	15,538

Table 4
Mutual Funds' Nontraditional Share

This table reports the results of cross-sectional regressions of mutual funds' nontraditional share on portfolio manager's experience and fund characteristics

$$NTS\ share_i = \alpha_{objective(i)} + \beta \cdot Experienced\ manager_i + \gamma' X_i + \varepsilon_i$$

where each observation is the average of quarterly observations in a given year. Panel A reports the results for the full sample, while Panel B reports the results for the subsample of top 250 funds by par value of bond holdings. These funds account for about 90% of all mutual fund bond holding in the data. Manager experience is measured as of 2004. Experienced manager is a binary variable equal to 1 for funds with above median experience. *Retail share* is the share of retail share classes in fund assets. *Family retail share* is the share of retail share classes in fund family assets. Family ETF, equity, and taxable shares are the shares of ETFs, equity funds, and taxable bond funds in fund family assets. The omitted category is municipal funds. Objective fixed effects are included. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	2003	2004	2005	2006	2007	2008	2009	2010
				Panel A: All Funds				
Experienced manager	−0.002	−0.007*	−0.010**	−0.018***	−0.033***	−0.023***	−0.003	−0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
Log(TNA)	0.000	0.003*	0.004*	0.006*	0.006**	−0.001	−0.005*	−0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Log(Family TNA)	−0.001	0.000	−0.001	−0.002	0.000	0.002	−0.001	−0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Log(Fund age)	0.001	−0.005	−0.013**	−0.011*	−0.009	0.003	0.005	0.001
	(0.004)	(0.004)	(0.006)	(0.007)	(0.008)	(0.007)	(0.005)	(0.004)
Log(Family age)	0.003	0.005	0.003	0.006	−0.008	−0.018**	0.001	0.001
	(0.004)	(0.005)	(0.005)	(0.007)	(0.009)	(0.009)	(0.008)	(0.007)
Expense ratio	−0.012	0.452	−0.319	0.351	2.248	1.418	−1.361	−1.177
	(0.656)	(0.565)	(0.889)	(0.824)	(1.943)	(2.255)	(1.061)	(1.287)
Share of retail classes	−0.005	0.005	0.021**	0.020*	0.004	−0.009	0.014	0.021
	(0.011)	(0.008)	(0.009)	(0.010)	(0.013)	(0.012)	(0.014)	(0.014)
Family retail share	0.012	−0.000	−0.022*	−0.035**	−0.003	0.033*	−0.020	−0.031*
	(0.011)	(0.009)	(0.012)	(0.014)	(0.018)	(0.019)	(0.024)	(0.019)
Family ETF share	0.243	0.013	0.016	0.031	0.046	−0.106***	−0.114***	−0.096***
	(0.227)	(0.025)	(0.035)	(0.035)	(0.045)	(0.038)	(0.040)	(0.032)
Family equity share	−0.024	−0.004	−0.007	0.007	0.019	0.015	0.034	0.010
	(0.018)	(0.015)	(0.025)	(0.053)	(0.040)	(0.033)	(0.033)	(0.033)
Family taxable share	0.010	0.026	0.026	0.044	0.080*	0.091**	0.069*	0.031
	(0.019)	(0.017)	(0.026)	(0.053)	(0.048)	(0.040)	(0.036)	(0.032)
Constant	0.021	−0.003	0.051	0.040	0.031	0.035	0.027	0.045
	(0.020)	(0.018)	(0.034)	(0.058)	(0.044)	(0.035)	(0.037)	(0.035)
N	790	822	846	815	790	784	718	662
Adjusted R^2	0.289	0.306	0.316	0.272	0.182	0.171	0.093	0.062

(continued)

Table 4(continued)
Mutual Funds' Nontraditional Share

	2003	2004	2005	2006	2007	2008	2009	2010
	Panel B: Top 250 Funds							
Experienced manager	−0.007	−0.009	−0.017*	−0.028**	−0.037***	−0.014	0.007	0.009
	(0.007)	(0.008)	(0.009)	(0.012)	(0.013)	(0.012)	(0.011)	(0.007)
Log(TNA)	0.008*	0.004	0.003	0.012	0.007	−0.005	−0.012	−0.005
	(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.009)	(0.010)	(0.005)
Log(Family TNA)	0.001	0.002	0.005	−0.005	−0.008	−0.002	−0.006	−0.002
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.003)
Log(Fund age)	−0.001	−0.003	−0.014	−0.017	−0.012	−0.003	0.003	0.004
	(0.007)	(0.009)	(0.013)	(0.014)	(0.013)	(0.010)	(0.008)	(0.005)
Log(Family age)	−0.001	−0.000	−0.017	0.008	−0.006	−0.026**	−0.003	−0.000
	(0.015)	(0.013)	(0.015)	(0.016)	(0.018)	(0.013)	(0.012)	(0.009)
Expense ratio	2.939**	2.348*	1.119	1.014	1.645	−4.927	−2.495	2.199
	(1.332)	(1.374)	(1.690)	(2.084)	(3.770)	(3.318)	(3.816)	(1.790)
Share of retail classes	−0.029*	−0.006	0.006	−0.016	−0.043	−0.023	0.015	0.005
	(0.016)	(0.014)	(0.016)	(0.020)	(0.033)	(0.029)	(0.035)	(0.027)
Family retail share	0.046*	0.025	0.005	−0.040	0.006	0.074	−0.037	−0.026
	(0.025)	(0.024)	(0.024)	(0.031)	(0.049)	(0.057)	(0.064)	(0.044)
Family ETF share	−0.031	−0.058***	−2.894**	−1.663	0.143	−1.569*	−0.344	−0.029
	(0.023)	(0.022)	(1.378)	(1.184)	(1.379)	(0.807)	(0.361)	(0.199)
Family equity share	0.000	0.033	0.061	0.076	0.067	0.003	0.111	0.120*
	(0.027)	(0.030)	(0.042)	(0.072)	(0.093)	(0.089)	(0.087)	(0.061)
Family taxable share	0.045	0.051*	0.071	0.056	0.104	0.052	0.114	0.129*
	(0.028)	(0.028)	(0.048)	(0.089)	(0.120)	(0.120)	(0.097)	(0.067)
Constant	−0.084*	−0.067	0.008	0.036	0.121	0.225**	0.130	−0.035
	(0.044)	(0.047)	(0.057)	(0.084)	(0.086)	(0.111)	(0.102)	(0.053)
N	250	250	250	250	250	250	250	250
Adjusted R^2	0.343	0.464	0.444	0.393	0.199	0.241	0.076	0.082

Table 5
Mutual Fund Manager's Experience and Performance-Flow Relationship

This table reports the results of monthly performance-flow regressions:

$$\frac{Flows_{i,t}}{TNA_{i,t-1}} = \alpha_{objective(i),t} + \beta_1 \cdot R_{i,t-1} + \beta_2 \cdot R_{i,t-1} \cdot Experienced_{i,t-1} + \beta_3 \cdot Experienced_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t}$$

The sample of funds consists of bond and hybrid mutual funds. The sample period is 2003–2010. Fund flows are winsorized at the first and ninety-ninth percentiles. Objective-date fixed effects are included. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)
$\text{Ret}_{i,t-1}$	0.321***	0.312***	0.371***
	(0.053)	(0.053)	(0.062)
$\text{Log(TNA)}_{i,t-1}$	−0.003***	−0.003***	−0.003***
	(0.000)	(0.000)	(0.000)
$\text{Ret}_{i,t-1} \times \text{Log(TNA)}_{i,t-1}$	−0.008	−0.011	−0.012
	(0.007)	(0.007)	(0.008)
$\text{Experienced}_{i,t-1}$		0.001***	
		(0.000)	
$\text{Ret}_{i,t-1} \times \text{Experienced}_{i,t-1}$		0.051**	
		(0.021)	
$\text{Old}_{i,t-1}$			−0.000
			(0.001)
$\text{Ret}_{i,t-1} \times \text{Old}_{i,t-1}$			−0.020
			(0.025)
Constant	0.020***	0.019***	0.019***
	(0.001)	(0.001)	(0.001)
N	90,436	90,436	59,812
Adjusted R^2	0.050	0.050	0.051

Table 6
Nonlinearity of Experience

Panel A reports the results of cross-sectional regressions of mutual funds' nontraditional share during 2007 on fund manager's experience defined using different cutoffs

$$NTS\ share_{i,2007} = \alpha_{objective(i)} + \beta \cdot Experienced\ manager_i + \gamma' X_i + \varepsilon_i$$

Panel B reports the results of cross-sectional regressions of mutual funds' nontrational share during 2007 on returns and fund flows experienced by fund's manager(s) during 1998:

$$\begin{aligned} NTS\ share_{i,2007} = \alpha_{objective(i)} &+ \beta_1 \cdot Experience_i + \beta_2 \cdot Manager\text{'}s\ 1998\ returns_i \\ &+ \beta_3 \cdot Manager\text{'}s\ 1998\ returns \times Experience_i + \gamma' X_i + \varepsilon_i \end{aligned}$$

The sample of funds in Panel B consists of funds with at least one portfolio manager who managed a mutual fund during 1998. Fund manager's identity is fixed as of the end of 2004. For each manager, we measure the minimum returns and fund flows she experienced across all funds she managed during 1998. For team managed funds we then take the minimum across all managers with 1998 experience. *Experienced* dummy is equal to one for managers above the median of the distribution of experience within the sample of managers who managed during a fund during 1998. Same controls as in Table 4 are included but not reported. Objective fixed effects are included. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

Panel A: Nonlinearity of experience

	Started managing mutual funds before January 1						
	2001	2000	1999	1998	1997	1996	1995
Experienced manager$_i$	−0.002	−0.003	−0.004	−0.012*	−0.031***	−0.022***	−0.027***
	(0.012)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
N	790	790	790	790	790	790	790
Adjusted R^2	0.162	0.162	0.162	0.165	0.180	0.171	0.174

Panel B: 1998 outcomes

	Returns			Flows		
	(1)	(2)	(3)	(4)	(5)	(6)
Experienced$_i$	−0.068***	−0.050***	−0.041***	−0.063***	−0.042***	−0.036***
	(0.013)	(0.013)	(0.011)	(0.015)	(0.012)	(0.011)
Bottom half$_i$	−0.063***			−0.065***		
	(0.015)			(0.016)		
Bottom half$_i \times$ Experienced$_i$	0.074***			0.059***		
	(0.017)			(0.018)		
Bottom tercile$_i$		−0.051***			−0.048***	
		(0.016)			(0.015)	
Bottom tercile$_i \times$ Experienced$_i$		0.048***			0.027	
		(0.017)			(0.018)	
Bottom quintile$_i$			−0.038**			−0.029
			(0.017)			(0.022)
Bottom quintile$_i \times$ Experienced$_i$			0.036*			0.012
			(0.019)			(0.023)
N	512	512	512	506	506	506
Adjusted R^2	0.251	0.234	0.221	0.253	0.237	0.220

Table 7
Mutual Funds' Nontraditional Share and Local House Price Appreciation

This table reports the results of cross-sectional regressions of mutual funds' nontraditional share during 2007 on portfolio manager's experience and local house price appreciation

$$NTS\ share_i = \alpha_{objective(i)} + \beta_1 \cdot Experienced\ manager_i + \beta_2 \cdot \Delta HPI_i + \beta_3 \cdot \Delta HPI_i \cdot Experienced\ manager_i + \gamma' X_i + \varepsilon_i$$

where each observation represents the average across the 2007 quarterly observations. Manager experience is measured as of 2004. Experienced manager is a binary variable equal to 1 for funds with above median experience. Local house price appreciation is the annualized change in the HPI for the MSA in which the investment management firm is located. HPI is the all-transactions index from the Federal Housing Finance Agency. The same controls as in Table 4, including objective FEs, are included in the regressions but are not reported. Standard errors are adjusted for clustering by MSA. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
Experienced manager	-0.033^{***}	-0.033^{***}	-0.033^{***}	-0.014
	(0.009)	(0.009)	(0.009)	(0.018)
$\Delta HPI_{2005->2006}$	0.196^{*}			
	(0.115)			
$\Delta HPI_{2004->2006}$		0.232^{**}		
		(0.097)		
$\Delta HPI_{2003->2006}$			0.237^{**}	0.350^{*}
			(0.101)	(0.188)
Experienced $\times \Delta HPI_{2003->2006}$				-0.218
				(0.191)
Constant	0.017	0.018	0.021	0.010
	(0.056)	(0.054)	(0.053)	(0.054)
N	783	783	783	783
Adjusted R^2	0.183	0.189	0.190	0.191

Table 8
Performance-Flow Relationship in Variable Annuity versus Regular Mutual Funds

This table reports the results of monthly performance-flow regressions for variable annuity versus regular mutual funds:

$$\frac{Flows_{i,t}}{TNA_{i,t-1}} = \alpha_{objective(i),t} + \beta_1 \cdot Ret_{i,t-1} + \beta_2 \cdot Ret_{i,t-1} \times VA_i + \beta_3 \cdot VA_i + \varepsilon_{i,t}$$

The sample consists of all funds with objective information in CRSP Mutual Fund Database. The sample period is January 2009–June 2013. Fund flows are winsorized at the first and ninety-ninth percentiles. Objective-month date fixed effects are included in all specifications. Columns 1-2 estimate pooled regressions across variable annuity and regular mutual funds. Columns 3-4 estimate separate performance-flow regressions for variable annuity funds in column 3 and regular mutual funds in column 4. Standard errors are adjusted for clustering by fund. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	Pooled		Mutual fund	Variable annuity
	(1)	(2)	(3)	(4)
Variable annuity$_i$	0.007**	0.007**		
	(0.003)	(0.003)		
Log(TNA)$_{i,t-1}$×Variable annuity$_i$	−0.008***	−0.008***		
	(0.000)	(0.000)		
Log(TNA)$_{i,t-1}$×Mutual fund$_i$	−0.006***	−0.006***		
	(0.000)	(0.000)		
Ret$_{i,t-1}$×Variable annuity$_i$	0.056***	0.072***		
	(0.016)	(0.019)		
Ret$_{i,t-1}$×Mutual fund$_i$	0.113***	0.129***		
	(0.017)	(0.020)		
Ret$_{i,t-1}$×Log(TNA)$_{i,t-1}$		−0.004*		
		(0.002)		
Log(TNA)$_{i,t-1}$			−0.006***	−0.008***
			(0.000)	(0.000)
Decile 1			−0.003***	−0.001
			(0.001)	(0.002)
Decile 2			−0.003***	0.002
			(0.001)	(0.001)
Decile 3			−0.003***	−0.000
			(0.001)	(0.001)
Decile 4			−0.003***	−0.000
			(0.001)	(0.001)
Decile 5			−0.006***	−0.002*
			(0.001)	(0.001)
Decile 7			−0.000	−0.002*
			(0.001)	(0.001)
Decile 8			0.000	−0.002**
			(0.001)	(0.001)
Decile 9			0.003***	−0.001
			(0.001)	(0.001)
Decile 10			0.013***	0.003
			(0.001)	(0.002)
Constant	0.045***	0.044***	0.046***	0.053***
	(0.001)	(0.001)	(0.001)	(0.003)
N	546,305	546,305	437,405	108,900
Adjusted R^2	0.062	0.062	0.064	0.083

Table 9
Insurance Companies' Nontraditional Share

Each column reports the results of a cross-sectional regression of insurance companies' nontraditional share on firm characteristics

$$NTS\ share_i = \alpha + \beta' X_i + \varepsilon_i$$

where each observation represents an insurance group. We aggregate holdings across all insurance firms within a given group, and then for each insurance group average quarterly observations within a given year. We report the results for all insurers in Panel A and for the top 100 in Panel B. Size is the log of the par value of the bond portfolio. Strong rating is a binary variable equal to one for firms whose 2003 AM Best financial strength rating is above the median. At the insurance firm level, external manager is a binary variable equal to one for firms whose bond portfolios are managed by unaffiliated external managers. An insurance company and an asset management firm are considered to be unaffiliated if they have different ultimate parents in Capital IQ. At the group level, external manager is the asset-weighted average across subsidiaries. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	2003	2004	2005	2006	2007	2008	2009	2010
Panel A: All Insurers								
Size	0.003***	0.003***	0.004***	0.004***	0.004***	0.004***	0.002**	0.002**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Life	0.008**	0.006**	0.008**	0.010**	0.011***	0.012***	0.014***	0.013***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Capital/Assets$_{2003}$	−0.018**	−0.014*	−0.009	−0.013	−0.016	−0.026**	−0.030**	−0.022**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.011)	(0.014)	(0.011)
Strong rating	−0.001	−0.002	−0.001	0.001	0.002	−0.000	−0.002	−0.001
	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Mutual	0.001	−0.001	−0.004	−0.004	−0.005	−0.005	−0.006	−0.005*
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
External manager	0.008**	0.007***	0.006**	0.007**	0.010**	0.006	0.003	0.000
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Constant	0.004	0.001	−0.004	−0.005	−0.007	0.003	0.015	0.011
	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)	(0.012)	(0.011)
N	876	810	750	713	649	636	622	592
Adjusted R^2	0.063	0.089	0.077	0.078	0.081	0.093	0.065	0.076
Panel B: Top 100 Insurers								
Size	−0.001	0.003	0.006**	0.006	0.008**	0.008*	0.006	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)
Life	0.005	−0.006	−0.012	−0.012	−0.007	−0.014	−0.014	−0.008
	(0.008)	(0.008)	(0.014)	(0.019)	(0.018)	(0.021)	(0.015)	(0.012)
Capital/Assets$_{2003}$	−0.078**	−0.091***	−0.124***	−0.128**	−0.107*	−0.116*	−0.115**	−0.097**
	(0.034)	(0.031)	(0.046)	(0.060)	(0.058)	(0.060)	(0.052)	(0.038)
Strong rating	0.001	0.000	−0.003	−0.006	−0.006	−0.018	−0.013	−0.009
	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.011)	(0.010)	(0.007)
Mutual	−0.007	0.001	0.002	0.008	0.002	−0.008	−0.010	−0.008
	(0.006)	(0.007)	(0.010)	(0.016)	(0.019)	(0.020)	(0.017)	(0.012)
External manager	−0.012	−0.007	−0.016*	−0.017*	−0.014	−0.024*	−0.022*	−0.017*
	(0.009)	(0.007)	(0.008)	(0.010)	(0.010)	(0.014)	(0.011)	(0.009)
Constant	0.059	0.020	0.008	0.022	−0.009	0.018	0.030	0.025
	(0.045)	(0.033)	(0.039)	(0.049)	(0.052)	(0.069)	(0.058)	(0.043)
N	100	100	100	100	100	100	100	100
Adjusted R^2	0.075	0.107	0.171	0.135	0.120	0.085	0.081	0.109

Table 10
Mutual Fund Transactions

This table reports the results of the regressions of quarterly net purchases of different types of securitizations on mutual fund flows

$$\frac{Net\ Purchases_{i,s,t}}{Holdings_{i,s,t-1}} = \alpha_{objective(i),t} + \beta_1 \cdot Inflows_{i,t} + \beta_2 \cdot Inflows_{i,t} \times Crisis_t + \beta_3 \cdot Outflows_{i,t} + \beta_4 \cdot Outflows \times Crisis_t + \varepsilon_{i,s,t}$$

where i indexes funds, s indexes types of securitizations, and t indexes quarters. Net purchases are scaled by lagged holdings and winsorized at the fifth and ninety-fifth percentiles. Fund flows are scaled by lagged total net assets, and are winsorized at the first and ninety-ninth percentiles. Inflows are equal to $max(0, \textit{Fund flows})$. Outflows are equal to $max(0, -\textit{Fund flows})$. Crisis is 2007Q3–2009Q2. In models 1, 3, 5, and 7, that do not include objective-date fixed effects, standard errors are adjusted for clustering by objective-date. In models 2, 4, 6, and 8, that include objective-date fixed effects, robust standard errors are reported. The bottom panel reports the p-values from the tests of proportional purchases and liquidations of different types of securitizations in response to fund inflows and outflows. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	ABS		GSE MBS		CMBS		NTS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.047**		−0.033**		−0.022**		−0.061***	
	(0.021)		(0.013)		(0.011)		(0.011)	
Inflows	1.151***	1.144***	1.213***	1.388***	1.185***	1.325***	0.838***	1.037***
	(0.133)	(0.121)	(0.124)	(0.119)	(0.145)	(0.141)	(0.134)	(0.127)
Inflows × Crisis	0.209	0.248	0.306	0.092	−0.170	−0.359	0.238	0.067
	(0.307)	(0.267)	(0.256)	(0.243)	(0.245)	(0.260)	(0.246)	(0.268)
Outflows	0.035	−0.059	−1.334***	−1.350***	−0.277	−0.049	−0.304*	−0.336**
	(0.191)	(0.169)	(0.179)	(0.180)	(0.211)	(0.205)	(0.174)	(0.167)
Outflows × Crisis	−1.114***	−0.537	−1.079***	−0.619	−0.396	−0.482	−0.360	0.086
	(0.346)	(0.377)	(0.398)	(0.394)	(0.342)	(0.326)	(0.325)	(0.302)
Constant	0.152***	0.161***	0.097***	0.087***	0.159***	0.150***	0.177***	0.161***
	(0.005)	(0.003)	(0.007)	(0.003)	(0.007)	(0.004)	(0.008)	(0.003)
N	13,132	13,132	17,779	17,779	12,570	12,570	14,125	14,125
Adjusted R^2	0.022	0.068	0.034	0.081	0.019	0.060	0.017	0.086
$\beta_{in} = 1$	0.26	0.24	0.09	0.00	0.20	0.02	0.23	0.77
$\beta_{in} + \beta_{in \times crisis} = 1$	0.19	0.10	0.02	0.02	0.93	0.88	0.71	0.66
$\beta_{out} = -1$	0.00	0.00	0.06	0.05	0.00	0.00	0.00	0.00
$\beta_{out} + \beta_{out \times crisis} = -1$	0.78	0.23	0.00	0.01	0.22	0.06	0.22	0.00
Objective×date FEs		✓		✓		✓		✓

Table 11
Insurance Company Transactions

This table reports the results of the regressions of quarterly net purchases of different types of securitizations by insurance companies

$$\frac{Net\ Purchases_{i,s,t}}{Holdings_{i,s,t-1}} = \alpha_{life(i),t} + \beta_1 \cdot Growth_{i,t} + \beta_2 \cdot Growth_{i,t} \times Crisis_t$$
$$+ \beta_3 \cdot Contraction_{i,t} + \beta_4 \cdot Contraction_{i,t} \times Crisis_t + \varepsilon_{i,s,t}$$

where i indexes insurance groups, s indexes types of securitizations, and t indexes quarters. Net purchases are scaled by lagged holdings and winsorized at the fifth and ninety-fifth percentiles. Change in the overall par value of the fixed income portfolio is winsorized at the first and ninety-ninth percentiles. *Growth* is $max\left(0, \frac{\Delta Bond\ holdings_{i,t}}{Bond\ holdings_{i,t-1}}\right)$. *Contraction* is $-min\left(0, \frac{\Delta Bond\ holdings_{i,t}}{Bond\ holdings_{i,t-1}}\right)$. In models 1, 3, 5, and 7, that do not include type-date fixed effects, standard errors are adjusted for clustering by type-date. In models 2, 4, 6, and 8, that include type-date fixed effects, robust standard errors are reported. *, **, and *** indicate statistical significance at 10%, 5%, and 1%.

	ABS		GSE MBS		CMBS		NTS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.012*		0.003		−0.015**		−0.019***	
	(0.007)		(0.008)		(0.007)		(0.006)	
Growth	0.165***	0.160***	0.283***	0.282***	0.212***	0.203***	0.198***	0.180***
	(0.028)	(0.018)	(0.032)	(0.015)	(0.041)	(0.019)	(0.033)	(0.018)
Growth × Crisis	−0.052	−0.053	−0.020	0.012	−0.049	−0.029	−0.136***	−0.122***
	(0.044)	(0.038)	(0.053)	(0.030)	(0.049)	(0.039)	(0.046)	(0.031)
Contraction	−0.136***	−0.138***	−0.177***	−0.200***	−0.154***	−0.146***	−0.058**	−0.055**
	(0.035)	(0.025)	(0.029)	(0.016)	(0.039)	(0.021)	(0.029)	(0.023)
Contraction × Crisis	−0.068	−0.065	−0.007	−0.045	−0.031	−0.028	−0.041	−0.023
	(0.070)	(0.059)	(0.040)	(0.036)	(0.065)	(0.039)	(0.036)	(0.039)
Constant	0.042***	0.044***	0.088***	0.089***	0.056***	0.053***	0.043***	0.039***
	(0.004)	(0.002)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
N	19,631	19,631	32,133	32,133	17,896	17,896	18,524	18,524
Adjusted R^2	0.014	0.025	0.047	0.074	0.028	0.064	0.023	0.059
Type×date FEs		✓		✓		✓		✓