

Brokers vs. Retail Investors:

Conflicting Interests and Dominated Products

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Abstract

I study how brokers distort consumer investment decisions. The market for retail convertible bonds offers a unique environment to study consumer investment decisions in a broker-intermediated setting. Using a novel data set, I find that consumers frequently purchase dominated bonds in this market – i.e., cheap and expensive versions of otherwise identical bonds exist in the market at the same time. Moreover, inconsistent with standard search models, consumers purchase more of the expensive bonds. The empirical evidence suggests broker incentives are partially responsible for the inferior investments as brokers earn a 1.12% point higher fee for selling the dominated bond. I rationalize the behavior of brokers and consumers in equilibrium by developing and estimating a search model. Consumer search is endogenously directed according to the incentives of brokers and a broker's ability to price discriminate across consumers based on the consumer's level of sophistication. I use the estimated model to disentangle and quantify the importance of search, consumer sophistication, and broker incentives. Aligning broker incentives with those of consumers' increases consumer risk-adjusted returns by 106bps, but does not resolve the primary friction in this market, consumer search. My estimated model allows for investigation of counterfactual scenarios surrounding the Dodd-Frank Act.

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1 Introduction

The prices and fees of seemingly identical financial products often differ drastically. Previous research documents price heterogeneity across mutual funds, mortgages, bonds and other financial products.¹ Does the observed price dispersion imply that some consumers are overpaying for investment opportunities? If so, what is driving this behavior? Sirri and Tufano (1998) and Hortaçsu and Syverson (2004) highlight the importance of search in a consumer’s investment decision process. However, consumer search does not happen in a vacuum. Broker intermediation plays a critical role in a consumer’s investment decision and search process. In 2010, 56% of American households sought investment advice from a financial professional.² Despite their prevalence, brokers may not be acting in the best interests of their clients. A broker may choose to subordinate her client’s interests for her own financial interests by directing her client to inferior products with high broker’s fees. While arguments such as these are abundantly available and have guided much of the policy response in the aftermath of the crisis (see section Section 913 of the Dodd-Frank Act), a rigorous empirical and theoretical investigation of this issue has been lacking. In this paper I fill this gap.

The paper has two goals. The first goal is to use novel data and a unique setting to show that consumers frequently purchase the dominated product in a market – i.e., cheap and expensive versions of otherwise identical products exist in the market at the same time – and that broker incentives are partially responsible for the inferior investments. The second goal is to rationalize the behavior of brokers and consumers in equilibrium by developing and estimating a search model. The model helps disentangle and quantify the importance of search, consumer sophistication, and broker incentives. I also use the model to investigate counterfactual scenarios surrounding the Dodd-Frank Act.

Several data challenges contribute to the lack of studies investigating these issue in detail. First, with most financial products, it is hard to find scenarios where one can easily compare products and rank one product as unambiguously dominating the other. Financial products, such as mutual funds, differ on a plethora of observable and unobservable characteristics, making direct comparisons

¹For examples, see Hortaçsu and Syverson (2004) and Elton et al. (2004) for the mutual fund industry, Gurun, Matvos and Seru (2013) for mortgages, Green Hollifield and Shürhoff (2007) for bonds, Duarte and Hastings (2012) for privatized social security plans, Christoffersen and Musto (2002) for money funds, and Brown and Goolsbee (2002) for life insurance.

²Source: Survey of Consumer Finances

of products tenuous. We may think that a consumer paying 2% for an S&P index fund is overpaying for that investment product. However, without observing all of the fund characteristics, making such claims is impossible. The problem is compounded once we allow for heterogeneity across consumer preferences and portfolio holdings. Some consumers may inherently prefer Vanguard funds to Fidelity funds or vice versa. Alternatively, different retirement plans may restrict the set of fund families consumers are eligible to hold. Second, little data have been available on the compensation of financial intermediaries. Did a consumer buy mutual fund XYZ or was he sold mutual fund XYZ by his broker?

I address these challenges by constructing a new retail bond data set covering reverse convertible bonds issued in the United States over the period 2008-2012. A reverse convertible is a fixed rate bond for which the final principal payment is convertible into shares of some pre-specified equity. The advantage of studying reverse convertible bonds over other financial products is twofold. First, reverse convertibles are completely characterized by a small number of dimensions, namely, a fixed coupon and an equity-linked principal payment. As a result, simultaneously issued reverse convertibles for which the payout of one reverse convertible is unambiguously dominated by another - the bond with the higher coupon - are easy to locate. Consider the following two nearly identical one-year reverse convertibles issued by JPMorgan Chase on June 30, 2008.³ One reverse convertible pays a fixed coupon of 11.25%, whereas the other pays a fixed coupon of 9.00%. Both reverse convertibles were sold to investors at a fixed par price of 100%. The final principal payment of both reverse convertibles is identical and linked to the share price of Microsoft Inc. If the price of Microsoft Inc. shares ever closes below \$22.68, the bond principal (for both bonds) is converted into equity where bond holders receive at maturity 35.27 shares of Microsoft Inc. for every \$1,000 invested.⁴ Figure 1 displays the hypothetical return to investors of the two products. Notice that the return of the 11.25% reverse convertible clearly dominates that of the 9.00%.⁵ However, in practice, consumers purchased more than 10 times as much of the dominated product. This example of a bank simultaneously issuing a dominated/superior product is not unique; I observe over 100 dominated/superior reverse convertibles in the data set.

³CUSIPS: 48123LAM6 and 48123LBR4

⁴The principal payment on both reverse convertibles is capped at par.

⁵The example of unambiguously dominated structured products is interesting when contrasted with the work of Carlin (2009) and C  lerier and Vall  e (2014). Banks could easily make the differences across products less salient by changing either the convertible price or the underlying equity; however, they often choose not to.

FIGURE 1: DOMINATED REVERSE CONVERTIBLE EXAMPLE

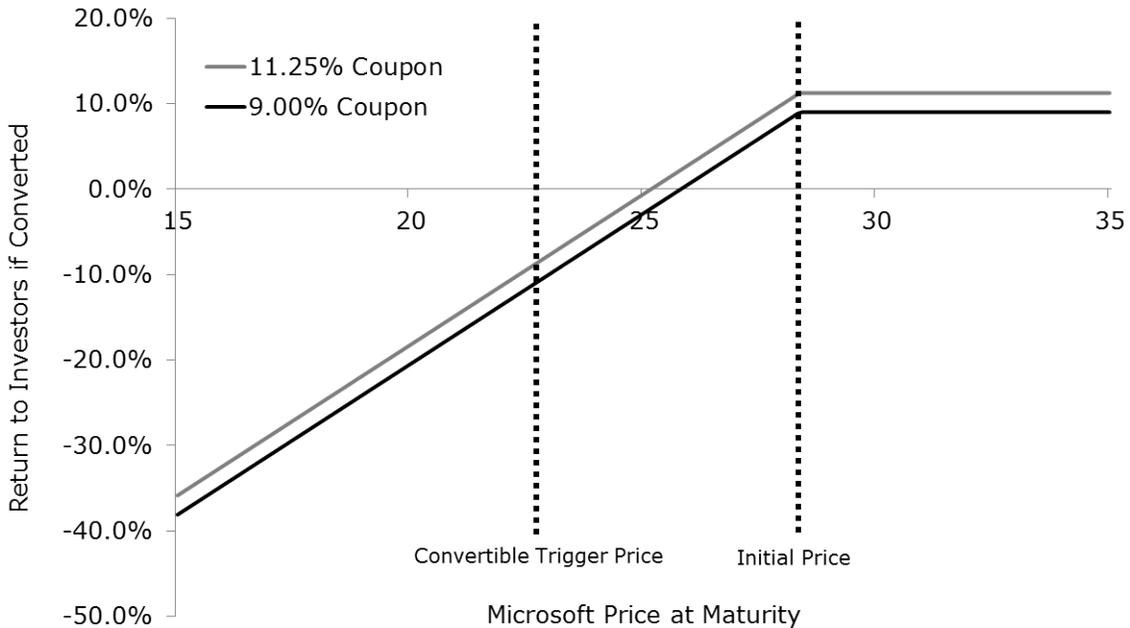


Figure 1 Notes: The figure displays the return to investors for two one-year reverse convertible bonds linked to the price of Microsoft Inc. that were issued by JPMorgan Chase on June 30th, 2008. The reverse convertibles pay monthly coupons of 9.00% and 11.25%, respectively. If the share price of Microsoft Inc. ever closes below the convertible trigger price of \$22.68 during the life of the reverse convertible, the issuer will pay the bondholder 35.27 shares of Microsoft Inc. per \$1,000 invested (\$1,000/Initial Price) rather than 100% of the principal amount invested. The final principal payment paid by the issuer is capped at par (100%). The above figure displays the final return to investors provided the principal has been converted into equity. Note that the 11.25% convertible always yields a 2.25% higher return than the 9.00% convertible.

The second advantage of studying reverse convertibles is that the Securities and Exchange Commission (SEC) requires all bond issuers to disclose the fees/commissions paid to brokers. Reverse convertible bond issuers, rather than consumers, compensate brokers with fees for selling reverse convertibles. In the previous JPMorgan example, JPMorgan paid brokers a commission of 3.09% for selling the worse 9.00% reverse convertible and only 2.15% for selling the better reverse convertible. This data therefore allows me to quantify the degree to which broker incentives influence consumer choice.

Using this new retail bond data set, I analyze the investment decisions of consumers in a broker-intermediated market. I find clear evidence of consumers buying unambiguously dominated financial products. Simultaneously issuing identical retail bonds at the same price with different interest rates/coupons such that the payout of one bond unambiguously dominates that of the other is a

common practice for investment banks. By simply buying the superior product, consumer risk-adjusted returns would have increased by 1.60% on average. What is more staggering, is that when both a dominated and superior product were available, consumers collectively purchased 16% more of the dominated product. The prevalence of dominated products suggests consumers purchasing the dominated product are not aware of the superior product. Hence, a consumer's investment decision problem is fundamentally a search problem. Search helps explain why consumers buy dominated products, but a standard search model⁶ predicts that consumers would purchase more of the better product, which runs contrary to what is observed in the data. I argue that financial product distribution rationalizes such behavior. The incentives of brokers do not always align with the incentives of consumers. Evidence from the retail bond data set indicates that, all else equal, consumers are more likely to buy products with higher brokerage fees, and products with higher brokerage fees have worse payoff profiles. On average, brokers earned a 1.12% point higher fee for selling dominated products.

The first part of my paper reveals three stylized empirical facts. First, the risk-adjusted returns of reverse convertibles exhibit substantial dispersion, and consumers often fail to purchase the best available financial product. The standard deviation of risk-adjusted returns in the data set is over 2.40%. Second, when better and worse products are available, consumers actually purchase more of the worse product. Third, the evidence suggests the incentives of brokers do not align with the incentives of consumers. All else equal, consumers collectively tend to purchase more products with higher fees, and products with higher fees have lower payoffs.⁷ I argue that the incentive and information asymmetry between brokers and consumers helps rationalize product issuance and the behavior of consumers.

In the second part of the paper, I rationalize the behavior of brokers and consumers in equilibrium by developing and estimating a search model. The model helps disentangle and quantify the importance of search, consumer sophistication, and broker incentives. In the model, consumers sequentially search for investment products with the aid of a broker. Brokers service their customer base by offering different products to each client. Brokers select products to offer each client based

⁶A sequential search model with random undirected search would predict that consumers purchase more of the better product.

⁷The finding that high fee products have worse risk-adjusted returns is consistent with evidence Gil-Bazo and Ruiz-Verdú (2009) find in the mutual fund industry.

on the quality of the financial product and the underlying broker's fee. In other words, broker profit maximization endogenously determines the distribution of products that consumers observe. Consumers ultimately decide whether to purchase the offered product or continue searching. Consumers differ in their level of financial sophistication (measured as search costs), and brokers utilize the full product space to price discriminate across consumers based on the consumer's level of financial sophistication.

The model introduces two frictions that are consistent with the empirical data. First, consumers must engage in costly search for products which explains why consumers might purchase inferior products. Second, brokers are incentivized to show high-fee products, which makes finding better products relative to worse products potentially harder for consumers. Broker's incentives in conjunction with consumer search help explain why consumers generally fail to purchase the best available products. I structurally estimate this model using the reverse convertible data set to determine whether the frictions in the model and associated costs are economically meaningful.

The model provides sharp insights that are useful in understanding consumer and broker behavior beyond just the reverse convertible market. First, the model helps to evaluate if the search costs and broker behavior that help rationalize the empirical facts documented earlier are "reasonable". Second, I can assess the total cost of each friction. For example, the model estimates suggest the average consumer spends over \$151 (in terms of the opportunity cost of time and the cost of delaying investment) searching for a \$10,000 investment. Third, I am able to show that aligning broker incentives with those of consumers' would increase consumer risk-adjusted returns increase by 106bps, but does not resolve the primary friction in this market, consumer search. Aligning the incentives of brokers helps consumers search more effectively. However, consumers still have to engage in costly search. This result speaks directly to policies passed as a part of the Dodd-Frank Act where the regulators may soon hold brokers to a fiduciary duty. Holding brokers to a fiduciary duty would force brokers to act in the best interest of their clients, which could result in consumers holding better financial products. The model suggests that while this would alleviate the consumer search problem, it would not eliminate it. Finally, my estimated model allows for investigation of other counterfactual scenarios surrounding the Dodd-Frank Act and issues related to optimal financial regulation in general.

This paper relates to the economics and finance literature regarding price and quality dispersion

in financial products. Previous work including but not limited to Massa (2000), Hortaçsu and Syverson (2004), Choi et al. (2010), Wahal and Wang (2011), and Khoran and Servaes (2012) indicate the law of one price may fail to hold in the mutual fund industry. Similarly, Anagol et al. (2012) find similar evidence in life insurance markets in India. One limitation of previous studies is that much of the observed dispersion in prices and quality of financial products could potentially be rationalized by unobserved product characteristics and preference heterogeneity. This paper offers the cleanest setting for studying retail financial markets. All consumers would be unambiguously better off purchasing the superior reverse convertible over the dominated convertible regardless of the consumer's preferences or portfolio.

Researchers have documented the potential broker and consumer information and incentive asymmetry arising in consumer finance (Livingston and O'Neal 1996, Mahoney 2004, Bolton et al. 2007, Bergstresser et al. 2009, Woodward and Hall 2012, Christoffersen et al. 2013). I find evidence consistent with Bergstresser et al. (2009), Anagol et al. (2012), and Christoffersen et al. (2013) suggesting that brokers may direct consumers into high-fee products. This paper builds on the preceding work by studying financial distribution in a clean setting in which identifying the conflict-of-interest problem is easier. In the data set, I observe all product characteristics as well as the fees paid to brokers. By directly comparing the dominated and superior products, I can isolate the effect of broker's fees on product issuance. The previous research suggests that underlying economic frictions in the market for reverse convertibles, search and broker incentives, apply to a much broader set of financial markets.

The remainder of the paper is laid out as follows. In Sections 2 and 3, I describe the reverse convertible data set and some fundamental features of the reverse convertible market. In Section 4, I analyze the reverse convertible data set and examine the characteristics of reverse convertibles purchased by consumers. In Sections 5 and 6, I develop and then structurally estimate a search model of financial distribution. I report the corresponding structural estimation results in Section 7. In Section 8, I use the structural estimates to quantify the inefficiencies in retail financial markets and evaluate the proposed regulatory response. Lastly, Section 9 concludes the paper.

2 Institutional Background: Reverse Convertibles

The empirical analysis focuses on the market for lightly structured retail bonds, specifically

equity reverse convertibles. A standard fixed-rate bond consists of a set of fixed coupon payments and final principal payment at maturity. Reverse convertible securities are similar to fixed-rate bonds except the final principal payment can be converted into shares of equity. At maturity, investors receive 100% of their principal provided that the underlying equity remains above the pre-specified convertible trigger price. If the equity falls below the convertible trigger price during the life of the bond, investors receive a fixed number of equity shares rather than the full principal amount.⁸ The value of the shares may be worth substantially less than the initial principal amount invested.

A reverse convertible essentially combines a standard fixed rate bond and an equity put option into one financial product. By buying a reverse convertible, the bondholder effectively sells the issuer a knock-in European put option. As illustrated in Figure 1, the bondholder is short a Microsoft Inc. knock-in put option that is struck at the initial share price of \$28.35 and knocks-in at the convertible trigger price of \$22.68. The issuer uses the premium earned from the knock-in put option to fund the broker's fee and the coupon paid to the bondholder.

2.1 The Market for Reverse Convertibles

Reverse convertibles offer a unique setting for understanding consumer investments and studying retail financial distribution. The financial industry largely recognizes reverse convertibles as the "Gold Standard" of retail structured products. Banks issued almost \$5 billion of reverse convertibles in the US in 2011 and \$50 billion globally, the bulk of which were purchased by retail investors.⁹ Reverse convertibles are largely an access product, allowing purchasers to sell equity options/volatility, which makes these products desirable for retail consumers rather than for companies and professional investors. Reverse convertibles provide investors with an opportunity to enhance the yield on a standard three month to two year fixed rate bond by taking some additional equity risk. Reverse convertibles pay a fixed, guaranteed, relatively high¹⁰ interest rate over the

⁸In practice two different common types of reverse convertibles exist: single observation and continuous observation. The previous discussion describes a continuous observation reverse convertible. The single versus continuous observation reverse convertibles differ with respect to the principal payment at maturity. A single observation reverse convertible is converted into equity if the equity price is below the convertible trigger price at maturity rather than if the equity price is ever below the convertible trigger price. Figure A-1 in the appendix walks through an example of a single observation reverse convertible.

⁹Source: Bloomberg

¹⁰The interest payments for the average reverse convertible in the sample exceeded ten percent per annum; the interest rate for a corresponding fixed rate bond was less than two percent over the same period.

life of the bond. To protect retail consumers, the SEC requires disclosure of the details of each reverse convertible issued, including broker's fees. Though relatively simple, reverse convertibles are often synonymous with structured products which are often criticized for their opaqueness and high costs.¹¹ The complexity and prevalence of reverse convertibles makes them of particular importance when analyzing some of the new proposed SEC broker regulations.

One of the primary advantages of studying reverse convertibles is that they are relatively easy to compare and contrast. Reverse convertibles are completely characterized by a small number of observable dimensions. A reverse convertible consists of an issuer, fixed coupon, broker's fee and equity put option. Additionally, it is common practice for banks to issue reverse convertibles that are unambiguously dominated. Banks frequently issue two reverse convertibles with the exact same risk and payout profiles; however, one reverse convertible will have a relatively high fixed coupon and a low broker's fee while the other has a relatively low fixed coupon and a high broker's fee. By studying the purely dominated/superior reverse convertibles, I am able to measure how consumers and brokers trade-off coupon and fees while controlling for all other product characteristics.

2.2 Reverse Convertible Market Structure and Distribution

The reverse convertible market consists of three players: product issuers, brokers and retail consumers. Product issuers, banks, create and issue reverse convertibles. Brokers purchase reverse convertible bonds from the product issuer and then sell the bonds to retail consumers.

Figure 2 illustrates the reverse convertible distribution process. Typically, at the beginning of each month product issuers create a suite of available reverse convertibles that will be issued at the end of the month. The issuer fixes all of the characteristics of each reverse convertible, including the broker's fee, at the beginning of each month.¹² Over the course of the month, issuers market available reverse convertibles to brokers who then solicit orders from retail consumers. At the end of the month all of the orders are accumulated and the reverse convertible is issued such that demand is completely satisfied. Issuers sell the reverse convertibles at a fixed par price of 100% minus the fixed broker's fee. Brokers then sell reverse convertibles to the end consumer at a fixed price of

¹¹See Stoimenov and Wilkens (2005), Henderson and Pearson (2011) and Szymanowska et al. (2009) for further details.

¹²Since the initial equity price is not known prior to issuance, the convertible trigger price is fixed and expressed as a percentage of the initial equity price.

par (100%).¹³ For each product sold, brokers earn the broker’s fee. Since issuers pay the fee, it represents a transfer from the issuer to the broker. Consequently consumers are ambivalent over the broker’s fee conditional on the risk and return of the product.

FIGURE 2: REVERSE CONVERTIBLE DISTRIBUTION

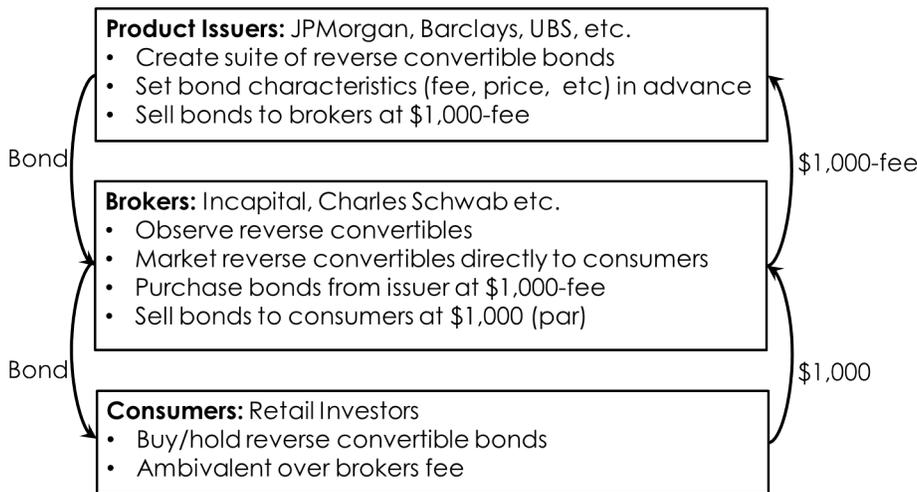


Figure 2 Notes: The figure displays the market structure/ distribution process of the reverse convertible market.

For regulatory reasons, issuers sell reverse convertibles through brokerage houses rather than selling them directly to consumers. SEC regulations such as the Securities Act of 1933 restrict the marketing of financial products to end consumers. Any materials used to market an SEC registered security (such as the reverse convertibles studied here) must be vetted for legal and compliance reasons and formally filed with the SEC. Since creating marketing materials can be a costly and lengthy process relative to the marketing period (typically one month), issuers do not market reverse convertibles directly to consumers.¹⁴ Rather, issuers choose to sell reverse convertibles to brokers who market them to consumers directly.

3 Data and Summary Statistics

The empirical analysis uses a new reverse convertible bond data set constructed for this paper.

¹³The majority of reverse convertibles are fixed price par offerings which means that they must be sold at a fixed price of par. On occasion, certain banks will issue reverse convertibles as variable price re-offerings which means they could theoretically be sold at a discount.

¹⁴Previous research such as Jain and Wu (2000), Cronqvist and Thaler (2004), Barber et al. (2005), Cronqvist (2006), and Hastings et al. (2013) find that advertising plays a critical role in the competition and demand for financial products.

The data set covers US, SEC registered, one year maturity reverse convertibles issued over the period 2008-2012. Issuance data, specifically the date, coupon, and size details are from Bloomberg and the Mergent Fixed Income Securities Database data sources. Details on each reverse convertible’s broker’s fees, initial equity share price and convertible trigger price were manually collected from the corresponding Form 424b filings found on the SEC EDGARS website. The data set is supplemented with equity volatility data from Option Metrics and Credit Default Swap (CDS) data from Markit.

Table 1 displays the summary statistics of the data set. The mean and median issuance size in the sample was \$1.64 million and \$665 thousand respectively. To ensure that the data set is limited to retail consumers, the largest 1% issuances (exceeding \$17.51 million) are dropped from the data set. On average, reverse convertibles paid a coupon of 10.50% per annum. The option premium measures the value of the put options embedded in each reverse convertible expressed as a percentage of the notional invested.¹⁵ The one year credit default swap (CDS) spread reflects the default risk for senior unsecured debt which corresponds to the issuer credit risk inherent to each reverse convertible bond.

TABLE 1: SUMMARY STATISTICS

Variable	Obs	Mean	Std.Dev.	Min	Max
Size (mm)	3066	1.64	2.62	0.00	17.51
Coupon	3066	10.50%	2.84%	3.24%	27.00%
Option Premium	3066	16.10%	3.90%	2.55%	42.90%
Fee	3066	2.24%	0.70%	0.00	6.75%
CDS Spread	2680	0.78%	0.60%	0.04%	9.20%

Table 1 Notes: Table 1 reflects US SEC registered one year equity reverse convertible issuance data over the period 2008-2012.

Reverse convertibles are almost exclusively issued by banks. Five banks: ABN Amro, Barclays Bank, JPMorgan Chase & Co, UBS and Royal Bank of Canada, dominate the issuance market for

¹⁵Option prices were calculated according to the Black Scholes (1973) formula for standard European options and the Reiner and Rubinstein (1991a 1991b) formulas for knock-in options. For a summary of the formulas see Haug (2007). I assume each underlying equity pays a constant dividend. The implied dividends are backed out from Option Metrics option price data.

one year reverse convertibles, making up over 80% of the market over the period 2008-2012. Apple Inc. served as the most popular underlying equity to link reverse convertibles to. Other popular underlying equities include Bank of America Corporation, General Electric Company, Caterpillar Inc., and JPMorgan Chase & Co.

4 What Type of Reverse Convertible Bonds Do Consumers Buy?

In this section, I examine the characteristics of reverse convertibles purchased by consumers. As alluded to in the introduction, consumers do not always purchase the best available convertibles. Using the new reverse convertible data set, I first examine the dispersion in reverse convertible returns. Second, I look at how often do consumers purchase inferior products. And third, I investigate how the incentives of brokers might drive this behavior. I use the prevalence of dominated products to isolate key variation in product returns and fees, which makes this a clean setting to study financial product distribution.

4.1 Dispersion in Reverse Convertible Returns

An extensive economics literature documents the substantial heterogeneity in the fees and prices of seemingly identical financial products. I find similar and perhaps the cleanest evidence of the failure of the law of one price in the market for reverse convertible bonds. Note that since reverse convertibles are issued at a fixed price of 100%, I do not observe price dispersion per se, but rather dispersion in the potential returns to investors. If two otherwise identical bonds are being sold with different coupons, this event is analogous to the same product being sold at different prices.

I calculate the dispersion in reverse convertible coupons conditional on all other observable bond characteristics. I examine the variation in reverse convertible coupons conditional on the value of the embedded put option and the issuer's CDS spread. Specifically, I estimate the linear regression

$$Coupon_j = \beta_0 + \beta_1 Option_Premium_j + \beta_2 CDS_j + Fixed_Effects \quad (1)$$

where I also include issuer, month, and equity fixed effects and control for the type of reverse convertible issued (single vs. continuous observation). Observations are reverse convertible bond

issuances. Theoretically, the above specification should control for all relevant reverse convertible characteristics. If the law of one price holds, we would expect to see little variation in coupons conditional on all other product characteristics.

Figure 3 plots the residuals from regression (1) and reflects dispersion in reverse convertible coupons conditional on observable product characteristics. Provided that specification (1) correctly captures all product characteristics, the observed dispersion in coupons is analogous to dispersion in investor risk-adjusted returns. Conditional on product characteristics, the reverse convertible market exhibits substantial heterogeneity in coupons. The standard deviation of conditional coupons is 1.14%. The results suggest the investor purchasing the best reverse convertible would earn a return that is over 10% higher than the investor purchasing the worst reverse convertible on a risk-adjusted basis. Relative to the average risk-free rate over the period studied, 0.60%, the dispersion in coupons is substantial. As a robustness check, I calculate return dispersion in terms of the risk neutral value of each reverse convertible and find further evidence supporting the heterogeneity in reverse convertible returns (see Figure A-2 in the appendix). The standard deviation of risk-adjusted returns is over 2.40%.

FIGURE 3: DISPERSION IN REVERSE CONVERTIBLE RETURNS

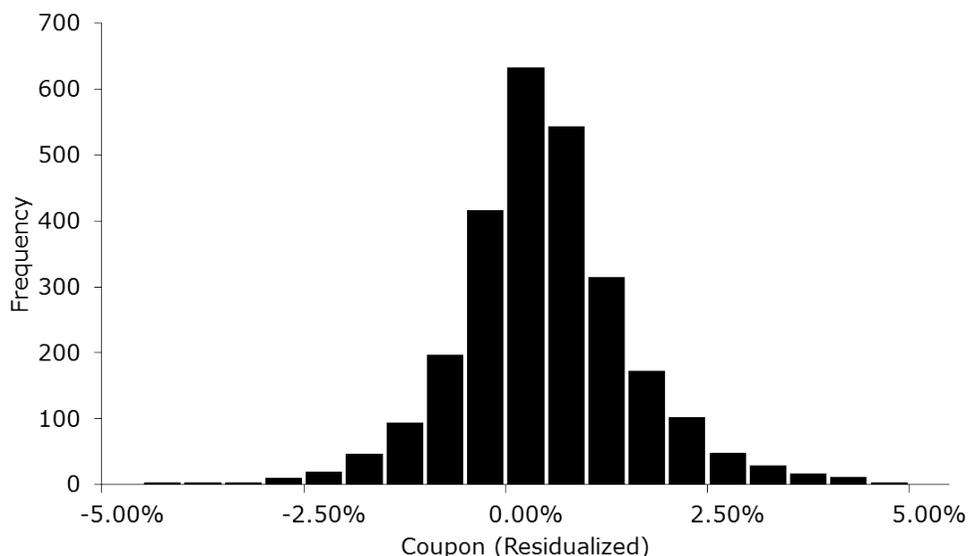


Figure 3 Notes: The figure displays dispersion in reverse convertible coupons. Specifically, Figure 3 plots the residual from the regression of reverse convertible coupons on all observable product characteristics.

The dispersion observed in Figure 3 stems from two potential sources. First, the observed dispersion may be “real” coupon dispersion such that the conditional returns of some reverse convertibles are simply higher than others. Second, the dispersion could be a function of unobserved product characteristics. In the case of mutual funds, previous research finds that unobserved fund characteristics are economically meaningful (Hortaçsu and Syverson 2004). The presence of unobserved product characteristics is likely less of a concern with reverse convertibles as their payouts are fully characterized by a small number of observable dimensions. To isolate “real” coupon dispersion from unobserved product heterogeneity, I examine the set of reverse convertibles that are either unambiguously dominant or are dominated by other reverse convertibles.

As discussed in the introduction, banks frequently issue identical reverse convertibles at the same price with two different coupon rates. I define a reverse convertible as being dominated if another reverse convertible exists with the same issuer, convertible payout, issue date, and price, with a higher coupon rate. In the data set of 3,066 reverse convertible bonds, 142 either dominate or are dominated by another reverse convertible.

Figure 4 plots coupon dispersion within dominated/superior products. I define a set of dominated/superior products as all products with the same issue date, issuer, price, and convertible payout. Figure 4 plots the distribution of $c_{i,j} - \bar{c}_j$. Here, i indexes the reverse convertible issuance and j indexes a set of dominated/superior products. By plotting $c_{i,j}$ relative to \bar{c}_j , I am able to perfectly control for all other product characteristics. Hence, Figure 4 plots the “real” coupon dispersion.¹⁶ Figure 4 also reflects the distribution of ex-ante and ex-post returns among reverse convertibles.

¹⁶Another way of constructing Figure 4 would be to use the residuals from the regression of product coupon with a fixed effect corresponding to each set of dominated products.

FIGURE 4: DISPERSION IN REVERSE CONVERTIBLE RETURNS (DOMINATED/SUPERIOR)

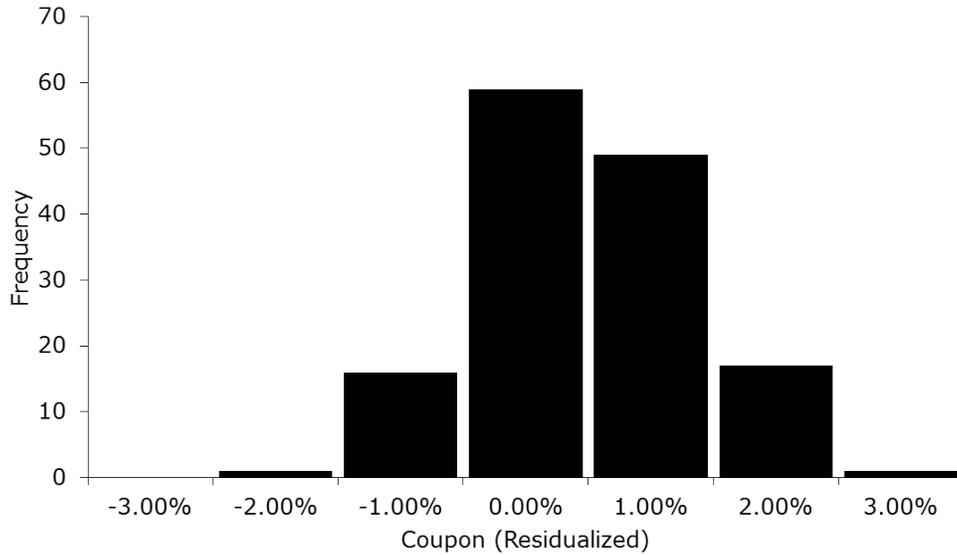


Figure 4 Notes: The figure displays dispersion in reverse convertible coupons among those convertibles that are either dominated or superior in the data set. Figure 4 plots coupon dispersion within dominated/superior products. I define a set of dominated/superior products as all products with the same issue date, issuer, price, and convertible payout. Figure 4 plots the distribution of $c_{i,j} - \bar{c}_j$. Here, i indexes the reverse convertible issuance and j indexes a set of dominated/superior products.

Figure 4 suggests a substantial amount of “real” coupon dispersion exists among reverse convertibles. The dispersion in Figure 4 cannot be a function of some unobserved product characteristic, because these products are otherwise identical. The standard deviation of returns within dominated/superior products is 0.90%. This result suggests unobserved product characteristics do not drive the bulk of the dispersion observed earlier in Figure 3.

4.2 Demand for Dominated Products

The market for reverse convertibles exhibits a substantial amount of “real” dispersion in returns/coupons that unobserved product heterogeneity cannot explain. The economic importance of the dispersion hinges on how often consumers purchase the inferior reverse convertibles.

Figure 5 Panels A-C plot the average characteristics of the dominated and superior reverse convertibles discussed in the previous section. On average, the coupon and subsequent return of the superior reverse convertible is 1.60% points higher than the corresponding dominated reverse convertible. Panel B indicates that, on average, consumers collectively purchased 16% more of the

dominated product. Not only are consumers buying dominated products, but they are also actually purchasing more of them relative to the superior product.

FIGURE 5: DOMINATED AND SUPERIOR PRODUCTS

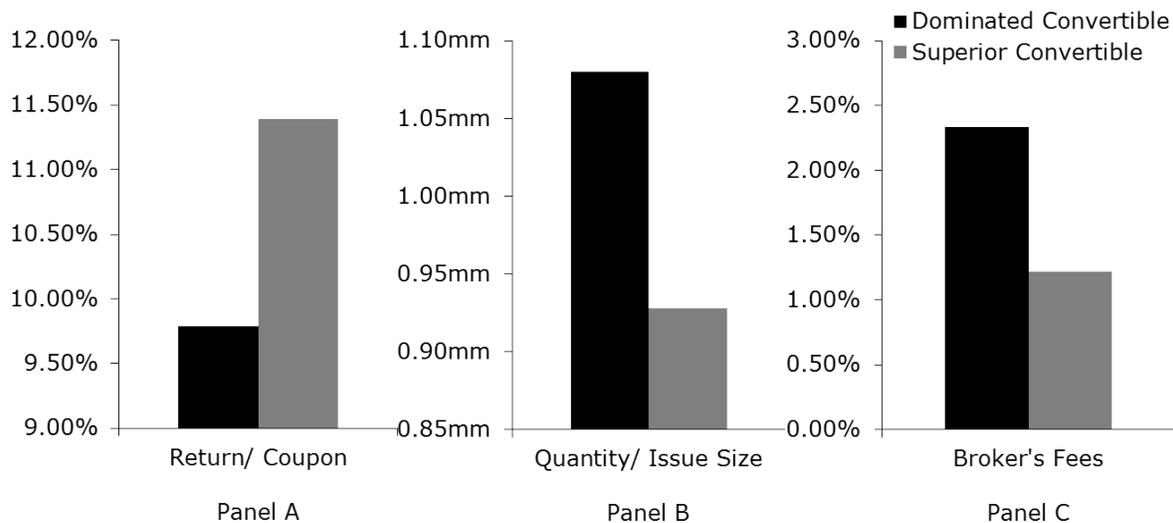


Figure 5 Notes: The figure displays the average characteristics of all of the dominated and superior reverse convertibles in the data set. The data set covers all US-issued, SEC-registered, one-year reverse convertible bonds. A reverse convertible is defined as dominated if a reverse convertible exists with the same issuer, issue date, price, underlying equity, and principal payment structure, with a higher fixed-rate coupon.

The result that consumers purchase more of the dominated product is critical because a standard search model would not predict this finding. In fact, a standard search model would predict the exact opposite: consumers should purchase more of the superior product. Consider a simple example in which two products exist, with one clearly superior to the other. In a simple undirected search model, consumers find each product with equal probability. When a consumer searches and finds the superior product, he simply purchases it and stops searching. If a consumer searches and finds the inferior product, consumers with low search costs continue searching for the superior product, whereas consumers with high search costs purchase the inferior product. Hence, consumers will purchase more of the superior product, provided consumers see both products with equal probability.¹⁷

Figure 5 illustrates the main points of the empirical and theoretical analysis of the paper. Panel A suggests the consumer's investment problem is fundamentally a search problem. I argue

¹⁷See Hortaçsu and Syverson (2004) for another example with a simple search model.

that consumers buy inferior reverse convertibles simply because they are not aware of the better convertible. However, Panel B suggests there may be more to the story beyond a simple search model. Consumers collectively purchase more of the dominated product. Last, Panel C shows the average fee paid to brokers for selling reverse convertibles. On average brokers, earned a 1.12% point higher commission for selling the dominated product. I argue and show more formally in the preceding section that the brokers and the incentives of brokers play a critical role in determining demand for reverse convertibles.

4.3 Product Distribution, Fees and Demand for Reverse Convertibles

The results from sections 4.1 and 4.2 indicate consumers often fail to purchase the best available product. I argue consumer search in conjunction with broker intermediation rationalizes such behavior. Brokers earn large and heterogeneous fees for selling different reverse convertibles. Figure 6 displays the distribution of broker's fees. Product issuers incentivize brokers with high fees to sell certain products.

FIGURE 6: BROKER'S FEES

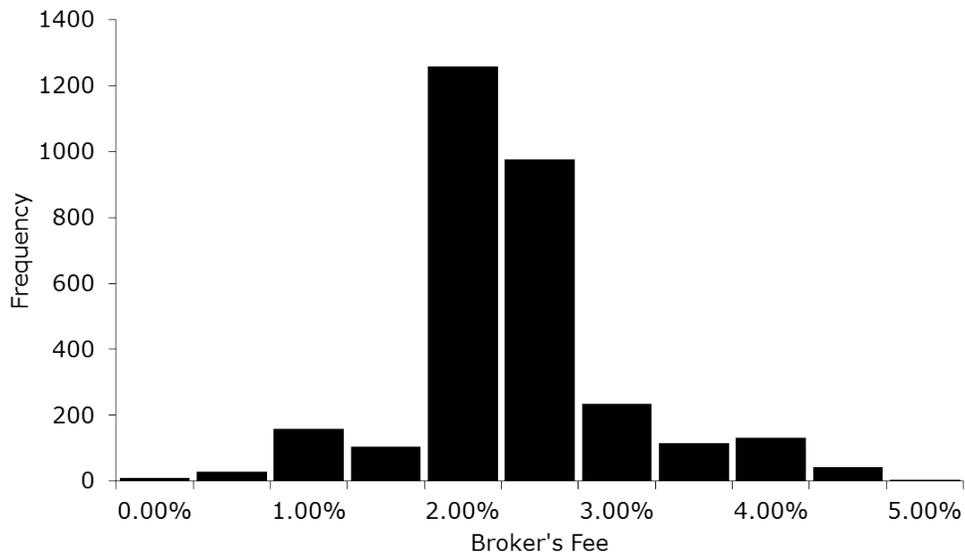


Figure 6 Notes: The figure displays the distribution of fees paid by issuers to brokers.

In this section, I analyze the relationship between product fees and demand for reverse convertibles. First, I estimate several reduced-form specifications to characterize the relationship between

product issuance, broker’s fees, and other product characteristics. I then look at the relationship between broker’s fees and other product characteristics. In general, the incentives of brokers do not appear to align with consumers. All else equal, consumers purchase more of high-fee product. Furthermore, products with high fees have worse payoffs on average.

4.3.1 Issuance Size vs. Product Characteristics

I first analyze the relationship between reverse convertible bond issuances and product characteristics. As will be discussed in detail, under certain assumptions, the following specifications and analysis can be interpreted in a simple linear demand framework.

Theoretically, both consumers and product issuers should value reverse convertibles based solely on their risk and return. In other words, under a risk-neutral framework, a reverse convertible should be valued based on its coupon, issuer credit risk, and embedded equity put option. I rely on two specifications to examine the relationship between product characteristics and issuance. I first regress bond-issuance size on the product-specific coupon, fee, embedded option premium, and issuer CDS spread:

$$Size_j = \beta Fee_j + \alpha Coupon_j + \gamma^{Opt} Option_Premium_j + \gamma^{CDS} CDS_j + Fixed_Effects \quad (2)$$

I also include issuer, month, and equity fixed effects and control for the type of reverse convertible issued (single vs. continuous observation). The observations are reverse convertible bond issuances such that j indexes a particular reverse convertible bond. One of the key variables of interest is the relationship between issuance size and broker’s fee. Recall that conditional on the risk and return of a product, consumers should be ambivalent over the broker’s fee.

As a robustness check, I estimate a corresponding demand specification in which I restrict the data set to the set of dominated/superior products. I estimate the regression of quantity issued on broker’s fees and coupon. I also include a fixed effect for each set of dominated/superior reverse convertibles:

$$Size_j = \beta Fee_j + \alpha Coupon_j + Fixed_Effects \quad (3)$$

The fixed effect captures all other product characteristics other than the product fee and coupon.

The linear specifications (1) and (2) help summarize the data. Under certain restrictions/assumptions, one could choose to interpret the above specifications as linear demand estimates. The main concern in interpreting either equation (1) or (2) in a causal demand framework is the potential endogeneity of the right-hand-side variables. One advantage of studying reverse convertibles is that in a risk-neutral framework, the fee, coupon, CDS, and option premium should capture all the relevant characteristics of a reverse convertible.¹⁸ Furthermore, when I restrict products to the set of dominated/superior products (eq. 3), I am able to control for all product characteristics. Also, the issuer typically sets the product characteristics one month in advance of a sale. For these reasons, any unobserved error term is likely to be idiosyncratic and uncorrelated with product characteristics. In some sense, the reverse convertible market offers a near perfect setting to study demand because I see identical products being sold at the same time at different parts of the demand curve.

Table 2 displays the regression estimates corresponding to equations (2) and (3). Columns (1)-(4) include the results for the full data set, whereas columns (5) and (6) display the regression results corresponding to when the data set is restricted to the dominated/superior products. The relevant coefficients not only have the expected sign, but are also statistically significantly different from zero. As expected, the product-issue size is positively correlated with coupon and negatively correlated with equity option premium and issuer credit risk. The results from column (3) indicate that a one percentage point increase in coupon is associated with a \$110,800 increase in issue size. Similarly, a one percentage point increase in equity put option premium is correlated with a \$61,800 decrease in issue size, whereas a one percentage point increase in issuer credit risk (CDS spread) is correlated with a \$431,400 decrease in issue size. Under a risk-neutral framework, one would expect consumers to trade off coupon one for one with both CDS spread and option premium, such that $\alpha = -\gamma^{Opt} = -\gamma^{CDS}$. Overall, the results suggest consumers trade off coupon and option premium roughly one for one but appear relatively averse to credit risk. One potential explanation for this finding is that the data set covers the peak and aftermath of the 2008 financial crisis. With the collapse of Lehman Brothers and Bear Sterns, consumers may have been more sensitive to the default risk of investment banks.

¹⁸One might also be concerned with the potential marketing/advertising of these products. SEC regulations require that any special marketing materials be filed with the SEC. Given the cost of marketing these products and the relatively short offering periods, no special marketing materials were filed for any of the reverse convertibles in the sample. Each convertible was marketed to consumers with the prospectus, which formally lays out the details of the security.

TABLE 2: ISSUE SIZE VS. PRODUCT CHARACTERISTICS

Dependent Variable	Size	ln(Size)	Size	ln(Size)	Size	ln(Size)
Broker's Fee	44.72*** (8.26)	28.48*** (4.70)	43.34*** (8.84)	28.95*** (5.01)	14.23* (7.91)	50.02*** (17.37)
Coupon	12.88*** (3.08)	12.57*** (1.61)	11.08*** (3.49)	10.20*** (1.77)	-4.31 (5.55)	6.10 (15.21)
Option Premium	-7.64*** (2.17)	-7.51*** (1.25)	-6.18** (2.49)	-5.69*** (1.35)		
CDS Spread			-43.14* (23.39)	-47.57*** (14.34)		
Continuous Obs.	-3.66*** (0.34)	-2.16*** (0.15)	-4.01*** (0.45)	-2.08*** (0.18)		
Dominated Products					X	X
Observations	3,066	3,066	2,680	2,680	143	143
R-squared	0.484	0.657	0.475	0.667	0.716	0.726

*Table 2 Notes: Table 2 displays the results from the regressions of quantity issued and broker's fees on the specified variables (eq. 2 and 3). Each specification includes issuer, underlying equity, and month fixed effects. Continuous observation is an indicator variable indicating the reverse convertible is a continuous rather than a single observation reverse convertible. Coupons and fees are measured such that 0.10 corresponds to a 10% coupon/fee. Quantity issued is measured in millions. Huber-White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

The regression results indicate demand is increasing in coupon and decreasing in CDS spread and option premium, but also that demand is increasing in broker's fees. In each specification, I estimate a positive and significant relationship between broker's fees and issue size, even when I restrict the data set to the set of superior/dominated products. The results from column (1) indicate that a one percentage point increase in broker's fees is correlated with a \$447,200 increase in issue size. Recall that conditional on the risk and return of a product, consumers should be apathetic toward broker's fees. One might be concerned that some omitted product characteristic that is positively correlated with fees and size might drive this relationship. However, I am able to control for all

product characteristics, especially when I restrict the data set to the set of dominated/superior products. These results suggest that brokers are more inclined to sell high-fee products.

4.3.2 Fees vs. Product Characteristics

The estimation results from the Table 1 suggest that all else equal, consumers buy more products with higher broker's fees. Because consumers are theoretically unaffected by the broker's fee, these results suggest brokers are directing consumers to higher-fee products. This finding raises concerns over the conflict of interest between brokers and consumers, especially if products with higher fees have lower returns and higher option premiums and issuer default risk. I examine this relationship further by estimating the following specification in which I regress the broker's fee on the set of product characteristics:

$$Fee_j = \beta_1 Coupon_j + \beta_2 Option_Premium_j + \beta_3 CDS_j + Fixed_Effects \quad (4)$$

I also include issuer, month, and equity fixed effects and control for the type of reverse convertible issued. Estimated coefficients $\beta_1 < 0$ and/or $\beta_2 > 0$, $\beta_3 > 0$ would be indicative of a conflict-of-interest problem.

As a robustness check, I again restrict the data set to dominated/superior products and regress broker's fees on the product coupon, and include a fixed effect for each set of dominated/superior reverse convertibles:

$$Fee_j = \beta_1 Coupon_j + Fixed_Effects \quad (5)$$

Restricting the data set again to dominated/superior products should help limit any concerns over the endogeneity of coupon and product fees.

Table 3 displays the estimation results corresponding to equations (4) and (5). The columns differ in terms of which co-variates are controlled for, whether the regression results are weighted by the square root of the issuance size, and the data set used. The results indicate that fees are negatively correlated with product coupon and positively correlated with equity option premium and issuer credit risk. The estimated coupon coefficients in all six specifications are negative and significant at the 1% level. The estimates indicate a one percentage point increase in coupon is associated with a 0.11% decrease in product fees. Similarly, a one percentage point increase in

option premium is correlated with a 0.07% increase in product fees. The estimates from column (4) imply a one percentage point increase in the issuer's CDS spread (issuer credit risk) is correlated with a 0.08% increase in product fees. Although the magnitude of the estimated coefficients is relatively small, the average level of fees in the data set is 2.20%.

TABLE 3: BROKER'S FEES VS PRODUCT CHARACTERISTICS

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Coupon	-0.10*** (0.01)	-0.11*** (0.01)	-0.10*** (0.01)	-0.10*** (0.01)	-0.53*** (0.09)	-0.68*** (0.07)
Option Premium	0.07*** (0.01)	0.08*** (0.01)	0.07*** (0.01)	0.07*** (0.01)		
CDS Spread			0.06 (0.04)	0.08* (0.05)		
Continuous Obs.	0.01*** (0.00)	0.00*** (0.00)	0.01*** (0.00)	0.00*** (0.00)		
Weighted		X		X		X
Dominated Products					X	X
Observations	3,066	3,066	2,680	2,680	143	143
R-squared	0.600	0.613	0.614	0.620	0.707	0.833

*Table 3 Notes: Table 3 displays the results from the regressions of broker's fees on the specified variables (eq. 4 and 5). Each specification includes issuer, underlying equity, and month fixed effects. The weighted specifications are weighted by the square root of the issuance size. Continuous observation is an indicator variable indicating the reverse convertible is a continuous rather than a single observation reverse convertible. Coupons and fees are measured such that 0.10 corresponds to a 10% coupon/fee. Huber-White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.*

Overall, the results from the empirical analysis confirm the existing concerns in the literature that the incentives of brokers do not align with the incentives of consumers. All else equal, consumers are more likely to buy reverse convertibles with high broker's fees. However, reverse convertibles with high fees tend to have worse payoffs. In this sense, brokers are incentivized to sell consumers inferior products.

5 Model

The heterogeneity in reverse convertible risk-adjusted returns raises the question: why do consumers buy inferior convertibles and why do issuers and brokers create and sell both good and bad convertibles? Furthermore, why are consumers actually more likely to purchase dominated products? This section develops a dynamic discrete time model of financial distribution that rationalizes consumer and broker behavior. The model is then structurally estimated and used to analyze and quantify the economic implications of the proposed broker regulations.

The key features of the model are motivated by the preceding empirical analysis and features of the reverse convertible market. The prevalence of dominated financial products suggests that the consumer's investment problem is fundamentally a search problem. Consumers buy dominated products simply because they are unaware of or unable to purchase better alternatives. In the model, consumers sequentially search over the product space with the aid of a broker. Brokers select a product to show each client based on the corresponding product specific broker's fee weighted by the probability the client purchases the product. In selecting products for a client, the objective of a broker is to maximize brokerage commissions rather than to maximize consumer utility. This formulation is supported by the results from the previous empirical section. Lastly, brokers utilize the product space to price discriminate across consumers, showing high fee dominated products to unsophisticated consumers and low fee superior products to sophisticated consumers. The key innovation in the model is that brokers endogenously direct the search of consumers according to the incentives of brokers and a broker's ability to price discriminate across consumers.

5.1 Model Overview

The model involves three types of market participants: consumers, brokers (serving as financial intermediaries) and product issuers. Although largely applicable to most retail financial products, the model is tailored to the distribution of reverse convertible bonds. Product issuers create reverse convertibles and then sell them through brokers to consumers. The actions of issuers and set of available reverse convertibles are taken as given. Rather, the model focuses on the endogenous interactions between brokers and consumers, taking the product space as given. Reverse convertibles are characterized by their payoff c (coupon), short equity put premium e , product issuer credit risk d , and broker's fee/commission f . All bonds are all sold at a fixed par price of 100%. Thus the

quadruplet (c, e, d, f) defines a financial product.

Each consumer possesses demand for exactly one reverse convertible bond. Consumers sequentially search over the product space one product at a time. Brokers direct the search process of consumers, informing consumers of the available products. Each period, a broker chooses which reverse convertible bond to show her consumer client. Brokers only show one reverse convertible to each consumer at a time. The consumer elects to either purchase the bond offered or continue searching for a new investment opportunity next period. Consumers can only purchase products offered to them by brokers. If the consumer purchases the bond j , he receives utility flow $\mathcal{U}(c_j, e_j, d_j)$ and his broker receives a fee f_j , that is paid by the product issuer. If the consumer decides to continue searching, he is matched with a new broker and is offered a new product next period.

5.2 Consumer Behavior

Each consumer must purchase exactly one reverse convertible bond. Consumers value financial products based on their risk and return. Product j with return c_j (coupon), put premium e_j , and issuer credit risk d_j generates consumer utility $u_j = \mathcal{U}(c_j, e_j, d_j)$. Utility is increasing in return and decreasing in put premium and issuer credit risk such that $\mathcal{U}_c > 0$, $\mathcal{U}_e < 0$ and $\mathcal{U}_d < 0$. The utility function is specified as a linear function of return/coupon, equity put premium, and issuer credit risk. Issuer credit risk is measured using the corresponding one year CDS spread.

$$u_j = \alpha \text{Coupon}_j + \gamma^{Opt} \text{Option_Premium}_j + \gamma^{CDS} \text{CDS}_j \quad (6)$$

This utility formulation is roughly consistent with the risk neutral fair value of a reverse convertible. If consumers value reverse convertibles according to the risk neutral prices, consumers should be willing to trade off coupon and equity put premium and issuer credit risk roughly one for one such that $\alpha = -\gamma^{Opt} = -\gamma^{CDS}$ (assuming no discounting).

There are two important things to note regarding the utility formulation. First, neither the price of a reverse convertible nor the broker's fee enters the consumer's utility function. This is because all reverse convertibles are sold at a fixed price of par (100%). The broker's fee is paid by the product issuer rather than the consumer. In this sense, the broker's fee represents the portion of profits shared between the issuer and the broker. Conditional on the risk and return of a product, consumers are apathetic regarding the broker's fee.

Second, the utility formulation implies that the products are vertically rather than horizontally differentiated. Notice that the utility specification does not include an unobserved product and consumer specific error term. Consequently, consumers possess a clear rank ordering over the product space.

Costly search prevents consumers from simply searching across all products and purchasing the product yielding the highest utility. There are two types of consumers, Searchers (sophisticated investors) and Non-Searchers (unsophisticated). By definition Non-Searchers always purchase the first product offered while Searchers may search across the product space. The fraction of Searchers in the population is denoted ω_S . Each period, Searchers must pay a search cost v_i in order to observe a new product offer from a broker. Search costs are heterogeneous across Searchers and are distributed $v_i \sim F(\cdot)$. Non-Searching consumers all face prohibitively high (infinite) search costs such that they never search across products. Consumer types (Searcher/Non-Searcher) reflect the information observed by brokers. Brokers observe a consumer's type and preferences but not his exact search cost. Thus brokers have incomplete information regarding the exact level of financial sophistication of each customer. Neither search costs nor consumer type are observed by the econometrician. As shown in the proceeding section, brokers will select different products to show different consumer types and will essentially price discriminate across Searching and Non-Searching investors.

Searching consumers sequentially search for the optimal investment among the discrete product space $\{u_1, u_2, \dots, u_n\}$. Products are numbered such that $u_j \leq u_{j+1}, \forall j$. While searching, a consumer receives an offer from a broker each period and then must elect to either purchase the offered bond or continue searching. If the consumer decides to continue to search he pays a search cost v_i and receives an offer from a new broker in the preceding period. All subsequent product offers are drawn i.i.d. from either the stationary distribution $H_S(\cdot)$ or the stationary distribution $H_{NS}(\cdot)$ depending on whether the consumer is a Searcher or Non-Searcher. As will be discussed in the proceeding section, the key innovation in the model is that the distribution of products observed by Searchers and Non-Searchers $H_S(\cdot)$ and $H_{NS}(\cdot)$ are endogenously determined based on the incentives of brokers. In equilibrium, consumer beliefs about $H_S(\cdot)$ and $H_{NS}(\cdot)$ are correct and completely rational. As discussed in the proceeding section, I focus on a stationary equilibrium in which the

distribution of offered products is constant over time.¹⁹ I abstract away from the broker/consumer matching process by assuming that conditional on type, brokers and consumers are ex-ante identical and are randomly assigned.

Let $V_S(u_j, v_i)$ denote the value function of a Searcher with search cost v_i that is offered a product yielding utility u_j . A consumer offered product j can either purchase the product or pay a search cost and continue searching. Formally the consumer's problem is²⁰

$$V_S(u_j, v_i) = \max \left\{ u_j, -v_i + \sum_{k=1}^n \rho_{k,S} V_S(u_k, v_i) \right\}$$

Purchasing the product j yields utility flow u_j while the expected utility of searching is $-v_i + \sum_{k=1}^n \rho_{k,S} V_S(u_k, v_i)$. Here $\rho_{j,S}$ reflects the probability a Searcher observes product j . The sets of offering probabilities $\rho_{1,S}, \rho_{2,S}, \dots, \rho_{n,S}$ are endogenously determined based on incentives of brokers. Collectively the probabilities $\rho_{1,S}, \rho_{2,S}, \dots, \rho_{n,S}$ form the distribution $H_S(\cdot)$.

Under this framework, consumers optimally search by adopting a reservation utility.²¹ A Searching consumer with search cost v_i searches until he is shown an investment product that exceeds his reservation utility $u^r(v_i)$. Consumers will optimally continue searching as long as the consumer's expected benefit of search is greater than his search cost. Suppose a consumer is offered product j yielding utility u_j , the consumers expected benefit of search is given by $\sum_{k=j+1}^n \rho_{k,S} (u_k - u_j)$ which is equal to the probability the consumer sees a better product than u_j weighted by the gain in terms

¹⁹Alternatively one can think of the market as clearing instantaneously.

²⁰The equivalent formulation with a continuous product space is given by

$$V(u_j, v_i, T) = \max \left\{ u_j, -v_i + \int_{\underline{u}}^{\bar{u}} V(u', v_i, T) dH_t(u') \right\}$$

where $[\underline{u}, \bar{u}]$ is the support of available products.

²¹See McCall 1970, Rogerson et al. 2005, and Hortaçsu and Syverson (2004) for a further discussion of search problems and a proof of the optimal strategy.

of utils.²² The optimal strategy is then²³

$$\begin{aligned}
\text{Continue Searching: } \underbrace{v_i}_{\text{Cost}} &\leq \underbrace{\sum_{k=j+1}^n \rho_{k,S}(u_k - u_j)}_{\text{Expected Benefit}} \\
\text{Purchase: } v_i &\geq \sum_{k=j+1}^n \rho_{k,S}(u_k - u_j)
\end{aligned} \tag{7}$$

The reservation utility is equal to the utility generated by product j , $u^r(v_i) = u_j$, such that $\sum_{k=j+1}^n \rho_{k,S}(u_k - u_j) \leq v_i \leq \sum_{k=j}^n \rho_{k,S}(u_k - u_{j-1})$. A consumer purchases the product if it exceeds his reservation utility, $u^r(v_i)$, otherwise he continues searching. An individual's optimal reservation utility, $u^r(v_i)$ is a weakly decreasing function of his search cost v_i . A consumer with zero search costs searches until he finds the product yielding the highest utility u_n while a consumer with infinite search costs (i.e. Non-Searchers) simply selects the first product offered. Let $G(\cdot)$ denote the stationary distribution of reservation utilities among Searchers in equilibrium.

In contrast, Non-Searching consumers simply select the first product offered to them by brokers. Non-Searchers can equivalently be thought of as consumers with infinite search costs. The probability a Non-Searcher observes a particular product j is denoted $\rho_{j,NS}$ and is endogenously determined based on broker profit maximization. The set of probabilities $\rho_{1,NS}, \rho_{2,NS}, \dots, \rho_{n,NS}$ from the distribution of products offered $H_{NS}(\cdot)$. Since brokers observe a consumer's type, the distribution of product offered $H_S(\cdot)$ and $H_{NS}(\cdot)$ will likely vary across types in equilibrium. In other words brokers may be more inclined to show Non-Searchers high fee inferior products while showing Searchers low fee superior products.

A couple of underlying assumptions in the model are worth noting. In the model framework, consumers know the distribution of product offerings $H_S(\cdot)$ and $H_{NS}(\cdot)$ (or equivalently $\rho_{j,S}$ and $\rho_{j,NS} \forall j$) but are unable to purchase a product without the aid of the broker. Although not applicable to all financial markets, this framework seems reasonable in the setting of reverse convertible

²²This formulation assumes consumers can recall and purchase products observed in prior periods; however, in practice consumers will never find it optimal to do so.

²³The equivalent optimal reservation strategy in the formulation with a continuous product space is given by

$$v_i = \int_{u^r}^{\bar{u}} (u' - u^r) dH_S(u')$$

where $[\underline{u}, \bar{u}]$ is the support of available products.

bonds. Reverse convertible bonds have short marketing periods (typically less than one month) and are SEC registered products which makes them costly to market directly to end consumers. Consequently, issuers do not market these products directly to consumers. The prevalence of dominated products indicates that search is a key component of the consumer's problem. Investor suitability regulations (FINRA Rule 2111) require that reverse convertible investors meet a certain level of financial sophistication, risk tolerance etc.. Hence, even though reverse convertible investors may not know the exact distribution of product offerings, they may still have realistic expectations over the distribution of product offerings based on previous experience and the prices of more transparent assets.

5.3 Broker Behavior

Brokers act as a liaison between the end consumers and the financial product issuers. Brokers observe the full scope of available products. Each period brokers offer each consumer an individual specific financial product tailored to the consumers level of sophistication/type. If the consumer purchases the product, the product issuer pays the corresponding broker a product specific fee. Fees f_j for a given product j are fixed but are heterogeneous across products.

Each issuer creates a suite of financial products available to and observed by all of the brokers. Let $\mathcal{J} = \{u_1, u_2, \dots, u_n\}$ denote the product space available to brokers. For each of her clients, the broker selects the product that maximizes her expected profits

$$\max_{j \in \mathcal{J}} E[\pi_{i,j}] \tag{8}$$

Offering product j to client i , yields an expected profit equal to the probability client i purchases product j multiplied by the returns from selling product minus the cost of offering the product. Brokers observe the preferences and types of their clients but do not observe each client's specific search cost. Recall that a Searcher purchases a product if and only if it exceeds his reservation utility while Non-Searchers always purchase the product offered. The probability product j exceeds a Searcher's reservation utility and thus the probability a consumer purchases the product is given by $G(u_j)$. The distribution of reservation utilities $G(\cdot)$ are endogenously determined based on the consumers optimal search strategy (14). The expected profit of offering product j to a Searching

consumer i is then

$$\mathbb{E}[\pi_{i,j,S}] = f_j G(u_j) + \eta_{i,j} \quad (9)$$

where $f_j G(u_j)$ is the broker's expected revenue and $\eta_{i,j}$ is a product/consumer specific marketing cost incurred by the broker. The cost term $\eta_{i,j}$ is unobserved (by the econometrician) and is assumed to be distributed T1EV. The expected profit of showing product j is increasing in the fees associated with the product and the utility generated by the product. The better the product, the higher the probability it will exceed a consumers reservation utility. Since Non-Searchers always purchase the product offered, the expected profit of offering product j to a Non-Searching consumer i is

$$\mathbb{E}[\pi_{i,j,NS}] = f_j + \eta_{i,j} \quad (10)$$

where f_j is expected revenue and $\eta_{i,j}$ is a product/consumer specific market cost. The cost term $\eta_{i,j}$ introduces broker/investor specific heterogeneity into the broker's profit function. Note that if $\eta_{i,j} = 0 \forall i, j$, brokers would always show the same product to Searchers and the same product to Non-Searchers. One can interpret $\eta_{i,j}$ cost of accessing and/or marketing a product to a particular client. Alternatively, η could be interpreted as broker error in assessing value of a product and the consumers type (Searcher/Non-Searcher).

A key assumption in the model framework is that brokers only show a client one product at a time and that each particular broker and client interact at most one time. These assumptions rule out any learning between brokers and clients. For tractability reasons, these assumptions simplify the broker's profit maximization problem to a static problem while the consumer's search problem remains dynamic. In practice these assumptions may be reasonable when applied to the reverse convertible setting. It seems unlikely that a broker would simultaneously show a superior and dominated product to a client. Similarly, a broker may be hesitant to show a client a superior product in a proceeding period after first showing them a dominated product or vice versa.

The probability that a broker selects product j to offer to a client of type T (Searcher or Non-Searcher), denoted ρ_{jT} , is given by

$$\rho_{j,T} = \Pr(\mathbb{E}[\pi_{i,j,T}] > \mathbb{E}[\pi_{i,k,T}] | \forall k \in \mathcal{J}_{-j})$$

Given the distributional assumption of the cost shock $\eta_{i,j}$, the probability that a broker selects product j follows the multinomial logit distribution

$$\rho_{j,S} = \frac{\exp(f_j G(u_j))}{\sum_{k=1}^n \exp(f_k G(u_k))} \quad (11)$$

$$\rho_{j,NS} = \frac{\exp(f_j)}{\sum_{k=1}^n \exp(f_k)} \quad (12)$$

The offering probabilities $\rho_{j,S}$ and $\rho_{j,NS}$ generate the distributions of available products $H_S(\cdot)$ and $H_{NS}(\cdot)$ observed by Searchers and Non-Searchers. Note that the distribution of reservation utilities $G(\cdot)$ and the distribution of product offerings $H_S(\cdot)$ and $H_{NS}(\cdot)$ are endogenously and simultaneously determined in equilibrium according to optimal consumer and broker behavior described in equations (7) and (8).

The probability a broker shows a particular product to a Non-Searcher is simply a function of the broker fees. The probability a broker shows a particular product is increasing the fees

$$\frac{\partial \rho_{j,NS}}{\partial f_j} = \rho_{j,NS}(1 - \rho_{j,NS}) > 0$$

Because of the unobserved cost shock, $\eta_{i,j}$, it is not always the case that the broker shows the highest fee product to a Non-Searcher. Rather, brokers, face consumer/specific marketing costs or make errors in assessing the value of the product and type of consumer such that probability a Non-Searcher sees a particular product is not degenerate.

The probability that a broker shows a particular product to a Searcher is a function of the product's fees as well as the probability that the client purchases the product. All else equal, the probability that a broker selects a particular product to show a client is increasing in the product's fees

$$\frac{\partial \rho_{j,S}}{\partial f_j} = G(u_j) \rho_{j,S}(1 - \rho_{j,S}) > 0$$

Brokers only earn the fee if the consumer purchases the product. The better the product offered, the more likely Searching consumers are to purchase the product. For this reason, the probability a broker selects a particular product to show a Searcher, all else equal, is increasing in the utility

generated by the product

$$\frac{\partial \rho_j}{\partial u_j} = f_j g(u_j) \rho_{j,T} (1 - \rho_{j,T}) > 0$$

where $g(\cdot)$ is the density corresponding to the distribution $G(\cdot)$. In this sense, the incentives of brokers and consumers are not totally misaligned. If the fees, f , and costs, η , were fixed across products, brokers would be incentivized to always offer products that generate the highest utility. However, the reduced form results from Section 4.3.2 suggest that fees and product utility are negatively correlated. Overall, Searchers are more likely to observe products with higher fees and that generate higher utility.

5.4 Equilibrium

I study a stationary pure strategy Bayes Nash equilibrium. In equilibrium consumers optimally search by employing the reservation strategy described by equation (7). Furthermore, consumer beliefs over the distribution of indirect utilities offered to Searchers and Non-Searchers, $H_S(\cdot)$ and $H_{NS}(\cdot)$, reflect the true distribution of product offerings generated from broker profit maximization. In equilibrium brokers maximize profits according to equations (9), and (10) where their beliefs over the distribution of reservation utilities reflect the true distributions generated by equation (7), $G(\cdot)$. The distribution of products observed by consumers, $H_S(\cdot)$ and $H_{NS}(\cdot)$, and the distribution of reservation utilities, $G(\cdot)$, are endogenously and simultaneously determined in equilibrium.

The distribution of search costs and consumer types in the population, market parameters and characteristics of available products are all assumed to be constant over time. Or alternatively, the market is assumed to clear instantaneously. The equilibrium is therefore stationary. Consequently, the distribution of product offerings and reservation utilities are constant over time.

6 Model Estimation

The search model described in Section 5 lends itself to structural estimation. Using the reverse convertible data set, I structurally estimate the search model. The model and estimation procedure most closely resembles that of Hortaçsu and Syverson (2004) and Hong and Shum (2006). The key parameters of interest are consumer preferences, the broker's profit functions, and the distribution of reservation utilities, consumer types and search costs.

The model is estimated using the reverse convertible market share level data described in Section 3. Each month and underlying equity defines a reverse convertible market and corresponding market share. For example, all one year reverse convertibles linked to Apple Inc. issued in December 2012 constitute a market. In total there are 498 markets with 1513 different reverse convertibles.²⁴

The model is estimated via maximum likelihood. The probability a consumer purchases product j is equal to the probability the broker shows the product to a consumer multiplied by the probability that the product's utility exceeds the consumer's reservation utility. The probability a consumer observes and purchases a bond depends on his consumer type which is observed by brokers but not the econometrician. Thus the probability that consumer i purchases product j is given by

$$\begin{aligned} \Pr(D_{ij} = 1) &= \omega_S \rho_{j,S} G(u_j) + (1 - \omega_H) \rho_{j,NS} \\ &= \omega_S \frac{\exp(\theta_S f_j G(u_j))}{\sum_{k=1}^n \exp(\theta_S f_k G(u_k))} G(u_j) + (1 - \omega_S) \frac{\exp(\theta_{NS} f_j)}{\sum_{k=1}^n \exp(\theta_{NS} f_k)} \end{aligned}$$

where $D_{i,j}$ is a dummy variable indicating that individual i purchased product j . Here the term ω_S reflects the probability a consumer is a Searcher, the term $\rho_{j,S}$ or $\frac{\exp(\theta_S f_j G(u_j))}{\sum_{k=1}^n \exp(\theta_S f_k G(u_k))}$ reflects the probability that a Searcher is shown product j , and $G(u_j)$ reflects the probability that product j exceeds a Searcher's reservation utility. I introduce the parameters θ_S and θ_{NS} as scaling parameter that scale the variance of the unobserved cost shock η . The parameters to be estimated in the model are the scaling parameters (θ_S, θ_{NS}) , the utility parameters corresponding to eq. (6), the distribution of reservation utilities $G(\cdot)$ among Searchers, and the distribution of consumer types ω_S . The distribution of consumer types (high and low) are estimated using a discrete mixing distribution similar to Heckman and Singer (1984).

I estimate the model using market share data. Hence, the dependent variable is the market share for each product which ranges from zero to one.²⁵ Note that from the market share data, I only observe bond purchases and do not observe individuals who were shown bonds but elected not to purchase them. A common problem related to demand estimation in the industrial organization literature is how to define and quantify the outside good/alternative which in this setting is not

²⁴Note that the original sample consists of 3,066 reverse convertibles. Markets consisting of only one reverse convertible are not used in the model estimation procedure.

²⁵As a robustness check shown in the appendix I also re-estimate the model where each observation is weighted by the market size.

purchasing a reverse convertible. I circumvent the outside good issue by simply estimating the observed conditional probabilities. I estimate the model via maximum likelihood where I condition on the probability that a consumer purchased a reverse convertible from that particular market. The corresponding likelihood used to estimate the model is given by

$$\Pr \left(D_{i,j} = 1 \mid \sum_{l=1}^n D_{i,l} = 1 \right) = \frac{\omega_S \rho_{j,S} G(u_j) + (1 - \omega_S) \rho_{j,NS}}{\sum_{l=1}^n [\omega_S \rho_{l,S} G(u_l) + (1 - \omega_S) \rho_{l,NS}]} \quad (13)$$

Estimating the conditional likelihood solves the outside good problem in this setting.

To facilitate estimation, I assume that consumers employ the same set of reservation strategies across all markets. In other words, $G(\cdot)$ is assumed to be constant across all markets. This assumption is equivalent to assuming that the distribution of search costs, consumer types and consumer beliefs over $H_S(\cdot)$ and $H_{NS}(\cdot)$ are constant across markets. For example, this implies that consumers searching for Apple linked reverse convertibles and Microsoft linked reverse convertibles hold the same beliefs over the distribution of available reverse convertibles. This assumption provides additional statistical power to estimate $G(\cdot)$, otherwise it would have to be separately estimated for each market. Although this assumption restricts consumer beliefs, it may not be unreasonable to think consumers searching for Apple or Microsoft linked reverse convertibles employ the same strategy. As a robustness check, in the Appendix I relax this assumption by re-estimating the model using only Apple linked reverse convertibles and find similar results.²⁶

The model is parametrized as follows. The utility function is specified as a linear function of coupon, option premium and the CDS spread according to equation (6). I also include issuer brand/fixed effects for the five largest issuers: ABN Amro, Barclays, JPMorgan, RBC and UBS.

Estimation of the model requires no additional assumptions regarding the parametric form of $G(\cdot)$. Following Barseghyan et al (2013), I flexibly estimate the distribution functions $G(\cdot)$ using a third order polynomial approximation to $\log G(\cdot)$.²⁷ I estimate polynomial approximations to $\log G(\cdot)$ rather than $G(\cdot)$ to ensure that the estimated distribution $\widehat{G}(\cdot)$ is strictly positive. However, I do not restrict the estimated distribution functions to be weakly increasing.²⁸ The variation in

²⁶See Table A-1.

²⁷Note that $G_H(\cdot)$ and $G_L(\cdot)$ are estimated using a smooth polynomial function while $G_H(\cdot)$ and $G_L(\cdot)$ are likely non-smooth in practice. Given that the distribution of available products is discrete $H_L(\cdot)$ and $H_H(\cdot)$, then the distribution of reservation utilities $G_H(\cdot)$ and $G_L(\cdot)$ will also be discrete according to the search model described in Section 5.

²⁸In the appendix, I estimate $G(\cdot)$ using a B-spline where I force $G(\cdot)$ to be positive and weakly increasing and find

the data helps identify the curvature of the reservation utility functions $G(\cdot)$. However, the scale of $G(\cdot)$ is not separately identified from θ_S in the above likelihood. The scale of $G(\cdot)$ is pinned down by the fact that all consumers purchase the best product which yields utility \bar{u} . In other words, no consumer continues searching if observes the best available product. Hence, $G(\bar{u}) = 1$.

The underlying data and model separately identifies the consumer utility and broker parameters as well as the observed distribution of reservation utilities. The utility formulation of the model allows for two normalizations. Due to its arbitrary scale and level, I normalize consumer preferences for coupon equal to one and the constant²⁹ to zero. Under this normalization, the utility parameters can be interpreted in terms of monetary value or percentage return.

Although each parameter of the model is jointly identified through the data, I provide a brief stylized discussion of the intuition behind the identification of the key parameters of the model. The preference parameters γ^{Opts} and γ^{CDS} measure how consumers trade off option premium and issuer credit risk (CDS) relative to coupon. Identification of preferences is best illustrated through the proceeding thought experiment. Suppose we observe a product with fees f , coupon c , and equity option premium e that has market share s . Now suppose we decrease the coupon from c to c' , $c' < c$. The question we are interested in is how much would the option premium have to decrease by from e to e' to keep the market share of the product unchanged at s . The compensating change in option premium identifies how consumers trade off option premium for coupon.

Intuitively, identification of the distribution of reservation utilities $G(\cdot)$ follows closely to that of the preference parameters. The conceptual experiment we would like to be able to run is to freely vary the coupon of a product and see how the corresponding product's market share changes, keeping all other products and product characteristics constant. Such variation allows us to trace out the curvature of the distribution of reservation utilities. The scale of $G(\cdot)$ is pinned down by the fact that all consumers purchase the best product which yields utility \bar{u} , i.e. $G(\bar{u}) = 1$.

The variation in consumer types is identified by variation in the distribution of product offerings across markets. Specifically, the variation in substitution patterns across markets identifies consumer types. Consider a market consisting of one clearly superior bond and one dominated bond in terms of utility. Now suppose an additional inferior bond is introduced into the market. We can identify

quantitatively similar results. See Figure A-3 for further details.

²⁹I included brand fixed effects for the five largest issuers: ABN Amro, Barclays, JPMorgan, RBC and UBS. The constant represents the brand effect for all other issuers.

the proportion of Searchers and Non-Searches based on how the market share of the superior bond changes when an additional inferior bond is introduced into the market. If the market share of the superior bond falls dramatically, that suggests those investors who initially purchased the superior reverse convertible were “lucky” Non-Searchers. If the market share of the superior bond does not change much, that suggests that those investors who initially purchased the reverse convertible were primarily Searchers. Although the preceding example is a bit stylized, variation in substitution patterns across markets is the key feature of the data that identifies consumer types.

7 Estimation Results and Analysis

7.1 Estimation Results

The maximum likelihood estimates are reported in Table 4. I first estimate the model under the assumption that all consumers are Searchers and then estimate the model allowing for the two types of consumers: Searchers and Non-Searchers. Columns (1) and (3) display the estimates for the one consumer type model while columns (2) and (4) report the estimates corresponding to the heterogeneous two consumer type model. As expected, the results indicate that consumer utility is decreasing in equity option premium and issuer credit risk (CDS). In all specifications, I estimate a negative and statistically significant relationship utility and the two measures of risk. The results from column (2) indicate that consumers are indifferent between a 1.00% point increase in coupon and a 1.033% point decrease in option premium. The results from column (3) imply consumers are willing to trade off a 1.00% point change in coupon for a 6.59% point decrease in the corresponding CDS spread. Recall that under a risk neutral framework consumers should be willing to trade off option premium and CDS spread roughly one-for-one with coupon. Just as with the reduced form results from Section 4, it appears that consumers are particularly sensitive to issuer credit risk.

In the two consumer type model, I also estimate the distribution of consumer types ω_S . The estimates in column (2) suggest that 88.3% of the population is comprised of Searchers while the remaining 11.7% of the population is comprised of Non-Searchers. The model estimates in both specifications suggest that the vast majority of consumers are Searchers. We can reject the null hypothesis that $\omega_S = 1$ in specification (2) but not in specification (4). These results suggest that brokers have a relatively limited ability to price discriminate across consumer types.

TABLE 4: STRUCTURAL ESTIMATION RESULTS

Variables	(1)	(2)	(3)	(4)
Coupon (α)	1	1	1	1
Option Premium (γ^{Delta}) -0.673***	-1.031***	-0.66**	-0.65***	
	(0.10)	(0.12)	(0.43)	(0.16)
CDS Spread (γ^{CDS})			-6.59***	-14.46***
			(2.35)	(3.01)
Scaling Parameter (θ_1)	72.35*	88.42*	39.67	51.96
	(39.14)	(56.39)	(24.35)	(44.25)
Scaling Parameter (θ_1)		15.18		42.10
		(29.28)		(80.08)
ω_S		88.70%***		98.04%***
		(4.02%)		(2.50%)
Heterogeneous Agents		X		X
Observations	1513	1513	1,227	1,227
Number of Markets	498	498	423	423

Table 4 Notes: Table 4 displays the maximum likelihood estimation results for the fully specified model. Standard errors are calculated using the observed Fisher Information Matrix. *, **, *** indicate significance at the 10%, 5% and 1% level.

7.2 Search Costs

The structural model provides additional quantitative insight into the underlying forces driving the market for reverse convertibles. The empirical evidence suggests that costly search prevents consumers from finding the superior reverse convertibles in the market. Using the model estimates, I am able to recover the distribution of search costs which provides us with an opportunity to determine whether or not the estimates are reasonable and/or economically meaningful.

I recover the search cost distributions as follows. First, from the estimation procedure I estimate the distribution of reservation utilities for Searchers, $\widehat{G}(\cdot)$. One of the empirical assumptions is that consumers use the same search strategies across markets; hence, $G(\cdot)$ is constant across markets.

Consistent with that assumption, I assume that each consumer’s belief over the distribution of indirect utilities offered reflect the empirical density of utilities offered, $\widehat{h}_S(\cdot)$. To calculate $\widehat{h}_S(\cdot)$, I first calculate the probability that a broker shows each product j to a client. Given the distribution of reservation utilities and corresponding profit parameters, I calculate $\rho_{j,S}$ for each product according to equation (11). Given the set of ρ s for each product, I then calculate the density of indirect utilities for observed product offerings for each consumer type $h_S(\cdot)$ via kernel density estimation giving each observed market equal weight.³⁰ Lastly, I calculate the distribution of search costs by inverting the equation

$$v_i = \int_{u^r}^{\bar{u}} (u' - u^r) dH_S(u') \quad (14)$$

Note that equation (14) is continuous product space equivalent to optimal reservation utility in the discrete formulation characterized by equation (7). Here I use the continuous product space formulation since consumer beliefs reflect the empirical density of offered products.

Figure 7 displays the estimated distribution of search costs for the single consumer type and two consumer type models. Both the one agent and two agent models produce similar estimates of the distribution of search costs. The estimated search costs from the two agent model suggest that roughly 50% of the population has search costs below 10bps. In other words over 50% of Searchers behave as the cost (in terms of time value) of soliciting an additional offer from a broker is less than \$10 for a \$10,000 investment. Furthermore, more than 75% of the population has search costs below 1.00%. Estimates from both models suggest that relatively small search costs can support the observed dispersion in returns.

³⁰Here $h_S(\cdot)$ and $h_{NS}(\cdot)$ are the densities corresponding to the distribution functions $H_S(\cdot)$ and $H_{NS}(\cdot)$. I estimate the density of the indirect utility of product offerings for each type of consumer using a Gaussian kernel and giving equal weight to each market. I use select the kernel bandwidth according to Silverman’s Rule of Thumb.

FIGURE 7: SEARCH COSTS

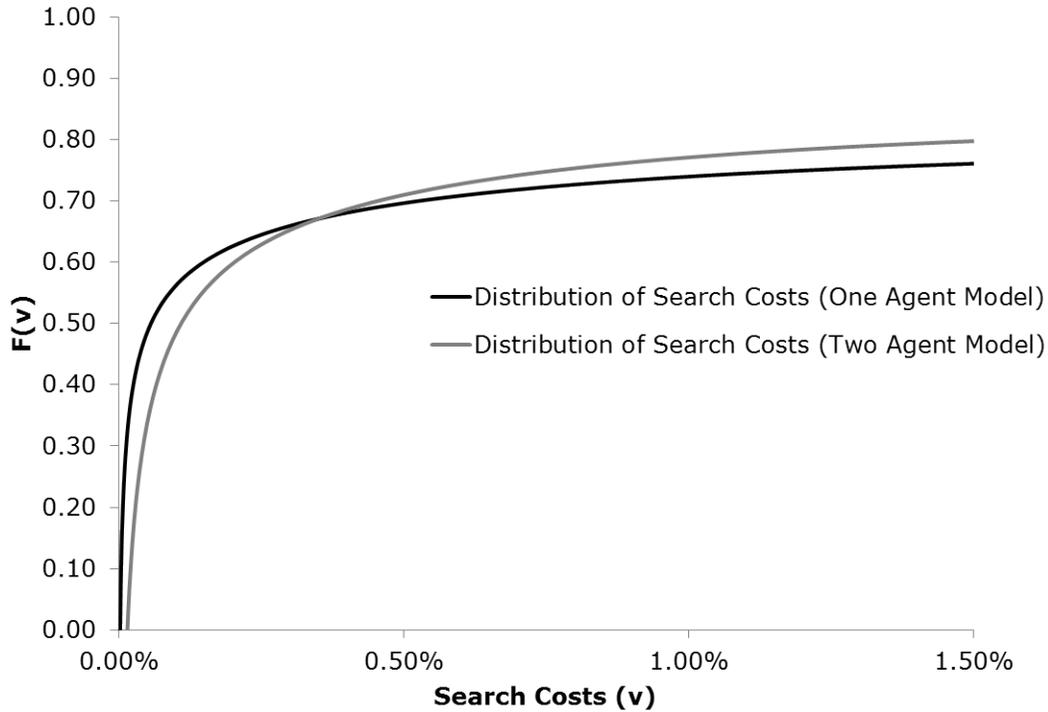


Figure Notes: Figure 7 displays the estimated distribution of search costs corresponding to the estimates in columns (1) and (2) of Table 4.

7.3 Broker Behavior

The consumer search problem is compounded by the fact that brokers are not incentivized to show consumers the best available products. The structural estimates help illustrate the incentives of brokers and assess the degree of price discrimination occurring in the reverse convertible market.

Consider the hypothetical market comprised of two nearly identical reverse convertibles where the payout of one dominates the payout of the other. One of the reverse convertibles, the superior reverse convertible, pays a coupon of 12% and a broker's fee of 1.00%. The other reverse convertible, the dominated reverse convertible, pays a coupon of 10% and a broker's fee of 3.00%. We can use the parameter estimates to determine the probability consumers of each type observe each product. Table 5 displays the probability consumers observe each product. Searchers observe both the superior and dominated products with roughly equal probability. However, brokers are 1.4x more likely to show a Non-Searcher the dominated product relative to the superior product. These

results help explain why not only consumers buy dominated products but why consumers may actually purchase more of dominated products.

TABLE 5: IMPLIED SEARCH PROBABILITIES

	Reverse Convertible 1	Reverse Convertible 2
Fee	1.00%	3.00%
Coupon	12.00%	10.00%
Prob. Observed by Searcher	0.51	0.49
Prob. Observed by Non-Searcher	0.42	0.58

Table 5 Notes: Table 5 displays the probability a broker shows a particular product to a Searcher and Non-Searcher in a two product market. Other than the coupon and associated brokers fee, Reverse Convertible 1 and Reverse Convertible 2 are assumed to be identical such that the payout of Reverse Convertible 1 dominates the payout of Reverse Convertible 2. Table 5 is computed using the parameter estimates from Column (2) in Table 4.

8 Discussion

Two economic forces/frictions appear to drive the existence and prevalence of dominated products. First, consumers must not be aware of or able to purchase the superior product. I model and argue that the consumer’s problem is fundamentally a search problem. Second, the consumers search problem is confounded by the fact that the incentives of brokers do not align with the incentives of consumers. As consumers search for new investment products, they are more likely to see high fee products. Hence the conflict of interest burdens consumers with excess search. The structural estimation results provide a way of quantifying the forces driving consumer behavior in an economically meaningful way. Both economic forces/frictions impact the distribution and total level of consumer and producer surplus. Understanding the costs associated with each force/friction provides insight into optimal financial regulation.

Building on the structural estimation results from the preceding section, I separately analyze the costs and inefficiencies generated by consumer search and the conflict of interest. I first examine the change in total and consumer surplus that would result if we were able to eliminate search costs. I then calculate the expected change in surplus associated if we were able align the incentives of brokers and consumers.

8.1 Search Costs

The fundamental friction in the model is search costs. If search costs were zero, consumers would simply search until they found the best product. Eliminating search costs would remove the market power currently held by brokers and product issuers.

I calculate the change in total search expenditure and the change in expected consumer returns if consumers had zero search costs. As discussed in the preceding section, I can calculate the implied distribution of search costs from the estimated distribution of reservation utilities and implied distribution of product offerings according to equation (14). A consumer's expected search expenditure is equal to his search cost multiplied by his expected number of searches. The expected number of searches follows a geometric distribution and is equal to one divided by the probability a consumer observes a product that exceed his reservation utility. The expected total search expenditure of a Searching consumer with search cost v_i is given by

$$\text{Search Expenditure}(v_i) = \frac{v_i}{1 - H_S(u^r(v_i))}$$

Table 6 reports the average change in search expenditures for consumers. To rule out potential outliers I examine the average search costs for consumers with search costs below 10% and assume no consumer searches more than 10 times.³¹ The estimates from the two agent model suggests that the average search expenditure for Searchers is 1.51%. Eliminating such search expenditures represents real surplus gains to the economy.

In the search model framework, the expected return of searching for a product is equal to a consumer's reservation utility $u_T^r(v_i)$. With zero search costs, all consumers would search until they found the best product generating utility \bar{u} . Consequently the average expected gain for Searchers is given by

$$\Delta \text{Expected_Return}_T = \bar{u} - \int_{-\infty}^{\infty} u' dG(u')$$

The term $\int_{-\infty}^{\infty} u' dG_T(u')$ reflects the average reservation utility or simply the average expected return for consumers.

Table 6 reports the average change in search expenditures and average change in risk-adjusted

³¹Recall that consumers with near zero search costs will search until they find the best available product. In this setting with 1513 products, that could result in an unrealistic number of searchers.

returns if all Searchers had zero search costs. On average, the one agent model suggests that the risk-adjusted of investors would increase by 5.83% points. Just under half of the gain in consumer returns (39%) is attributable to the decline in search expenditures. The remaining gain in consumer returns represents a transfer from brokers and product issuers to consumers.

TABLE 6: ECONOMIC IMPACT OF SEARCH COSTS

	One Agent Model	Two Agent Model
Avg. Search Expenditure	2.30%	1.51%
Avg. Change in Expected Return	5.83%	3.36%

Table 6 Notes: Table 6 displays the hypothetical gains to total and consumer surplus if all Searching consumers had zero search costs. To rule out any potential outliers we compute the average search expenditure and average change in expected return for Searchers with search costs below 10% per offer. We also assume that no consumer searchers more than 10 times. Table 6 is computed using the parameter estimates from Column (2) in Table 4.

This analysis reflects a partial equilibrium analysis in that the characteristics of available reverse convertibles and the actions of product issuers are fixed. If consumers had zero search costs that would eliminate all market power currently held by brokers and issuers. As issuers adapt to the new zero search cost environment, Nash Bertrand competition among issuers will drive them to create the best possible reverse convertible (in terms of utility) where issuers earn zero markups. In this sense, the estimates from Table 6 provide a lower bound on the change in expected consumer returns.

8.2 Broker Incentives

Brokers select the product that maximizes the broker's expected profit rather than the product that maximizes the utility of consumers. This second economic force burdens consumers with excess search. The preceding structural estimates help determine the cost associated with the asymmetric incentives between brokers and consumers.

Under the preceding framework, the probability a broker shows product j to a consumer is given by

$$\rho_{j,S} = \frac{\exp(f_j G(u_j))}{\sum_{k=1}^n \exp(f_k G(u_k))}, \quad \rho_{j,NS} = \frac{\exp(f_j)}{\sum_{k=1}^n \exp(f_k)}$$

I change the broker’s incentive structure by imposing that

$$\tilde{\rho}_{j,T} = \begin{cases} 1 & \text{if } u_j > u_l \forall l \in \mathcal{J}_{-j} \\ 0 & \text{otherwise} \end{cases}$$

Thus in a given market (defined in terms of the underlying equity and month), brokers must show the best available product in that market. For example, if a consumer is searching for a reverse convertible linked to Apple, the broker must show the client the best available Apple linked product in that month. The distributions of indirect utilities observed by consumers, $H_S(\cdot)$ and $H_{NS}(\cdot)$, is then generated by aggregating up the best products across each market. Note that even though consumers are always shown the best product in a given market, a consumer may still elect to continue searching across other markets. It is possible that the best product in a given market does not exceed the consumers reservation utility strategy.³²

Table 7 displays the average change in search expenditures and consumer risk-adjusted returns under the new policy. On average, search expenditures decline by 0.19%. The decline in search expenditures represent real increases in total economic surplus. Consumers capture most of the increase in surplus as consumer risk adjusted returns by 1.42% on average. The average risk free adjusted rate over the period studied was 0.60%. Consequently these represent relatively large gains in risk-adjusted returns. Just as with the preceding section, 8.1, this represents a partial equilibrium analysis in that the characteristics of available products are held fixed. Forcing brokers to always show the best available product in this manner would eliminate the market power currently held by brokers and issuers. For the same reasons described in Section 8.1, the estimates in Table 7 thus reflect a lower bound on the gain in expected consumer returns. As issuers optimally respond to the new broker policy, Nash Bertrand coupon/price competition among issuers will drive them to create the best possible product where issuers earn zero profits.

³²As discussed in the preceding section, I assume for the empirical analysis that all consumers adopt the same reservation utility strategy across all of the observed markets.

TABLE 7: ECONOMIC IMPACT OF BROKER INCENTIVES

	One Agent Model	Two Agent Model
Avg. Change in Search Expenditure	-0.19%	-0.17%
Avg. Change in Expected Return	1.42%	1.06%

Table 7 Notes: Table 7 displays the hypothetical gains to total and consumer surplus if brokers were forced to always show the best product available in a market to a Searching consumer. To rule out any potential outliers we compute the change in search expenditure and expected return for Searchers with search costs below 10% per offer. Table 7 is computed using the parameter estimates from Column (2) in Table 4.

8.3 Financial Regulations

Across the globe regulators are moving towards addressing the asymmetry between broker and consumer incentives. Australia, the United Kingdom, India, Norway, Finland, Denmark and the Netherlands all recently placed bans on commissions in the financial service industry.³³ With the Dodd-Frank Act, US regulators are moving in a similar direction. As part of the Dodd-Frank Act, US regulators may soon require brokers to act as fiduciaries for their clients which would obligate brokers to act in the best financial interests of their clients.

One way of implementing fiduciary duty would be to force brokers to always show the best available product in each market as discussed in the previous section (8.2). The results displayed in Table 7 suggest that consumer returns would increase by 1.42% on a risk-adjusted basis. Perhaps even more importantly, total surplus would increase by 0.19% points relative to the total amount invested. Relative to the average profits earned in the financial sector,³⁴ a 0.19% point gain represents a substantial increase in surplus.

The analysis has a few important caveats. In the model, brokers service their client base by helping clients sequentially search over the product space. In practice, brokers may also impact the total number of investors in the market. If brokers were to leave the market in the event of new financial regulations, the total provision of financial services may also decline. Also, high fees might be justified for clients that are expensive for brokers to service (i.e., clients that require additional

³³See King & Wood Malleons publication “Australia is Not Alone in Banning Commissions in Financial Services.” <http://www.malleons.com/publications/marketAlerts/2012/regulator-october-2012/Pages/Australia-is-not-alone-in-banning-commissions-in-financial-services.aspx>

³⁴For example, Hansen et al. (2014) find the average profitability of bank deposits in the US is approximately 2%.

education or hand-holding).

Although current regulations target the incentives of brokers, the results in Tables 6 and 7 suggest that addressing search costs may be more beneficial. In the context of the model, if consumers had zero search costs, the broker incentive problem becomes irrelevant. Current SEC regulations restrict the marketing of financial securities directly to consumers, which could harm consumer welfare. The results suggest such regulations could be counterproductive if they raise consumer search costs.

9 Conclusion

Economists and regulators have long been interested in the observed price dispersion in financial products. Does such price dispersion imply consumers are overpaying for investments? Using a new data set I find evidence that consumers frequently purchase products with dominated payoff structures. What's even more alarming is that when both a superior and dominated product are available, consumers are more likely to end up with the latter.

Previous research has pointed to consumer search as the mechanism supporting price heterogeneity and potentially dominated financial products. Consumer search helps explain why consumers buy dominated products, but a standard search model cannot explain why consumers are more likely to purchase the dominated product over the superior product. I argue that consumers are more likely to purchase dominated products because the product fee structure incentivizes brokers to sell dominated products; hence, the incentives of brokers differ from the incentives of consumers. The empirical evidence verifies the incentive asymmetry. All else equal, consumers are more likely to buy products with higher fees. And similarly, all else equal, products with higher fees have lower payoffs.

The finding that consumers frequently overpay for investments and the finding that the incentives of brokers do not align with consumers are likely not unique to the reverse convertible industry. This paper focuses on reverse convertibles because some features of the reverse convertible market make identifying dominated products and the incentives of brokers easier. I find little reason to believe that search and broker incentives do not play important roles in other financial markets. A vast literature discusses price heterogeneity in financial markets, which suggests consumers might be overpaying for investments in other product markets (Hortaçsu and Syverson 2004, Gurun et

al. 2013, and Green et al. 2007). Similarly, previous work, such as Livingston and O'Neal (1996), Mahoney (2004), Bergsteresser et al. (2009) and Christoffersen et al. (2013) details the potential conflict of interest arising in the mutual fund industry. The presence of dominated products and the broker/consumer incentive asymmetry prevalent in the market for reverse convertibles is more likely to be closer to the rule rather than the exception in financial markets.

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Appendix

FIGURE A-1: REVERSE CONVERTIBLE EXAMPLE (SINGLE OBSERVATION)

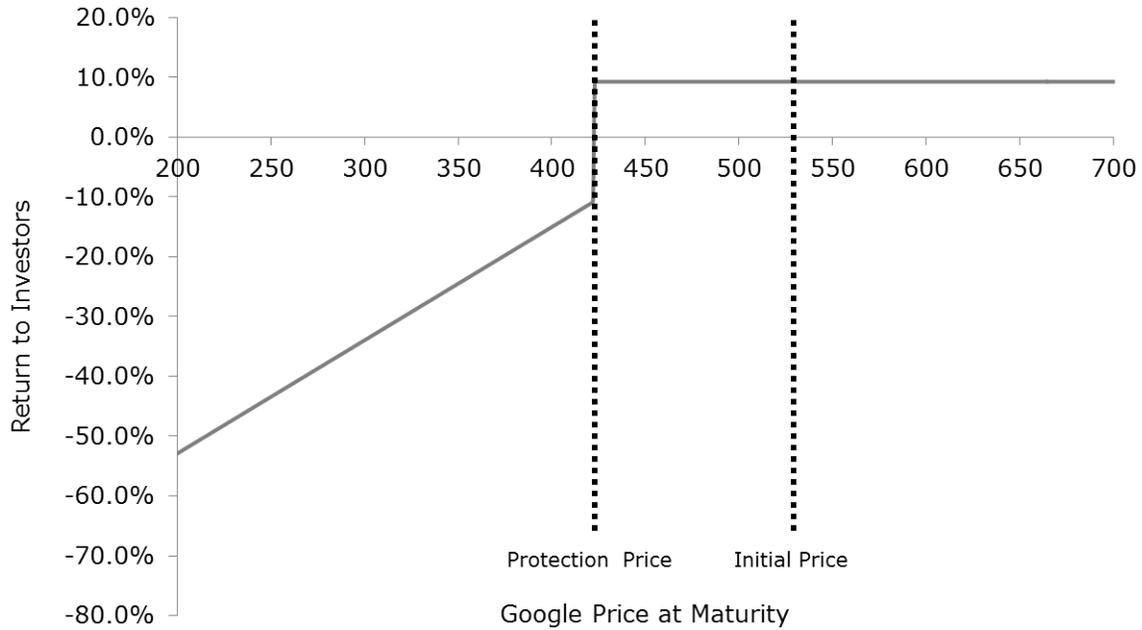


Figure A-1 Notes: The figure displays the return to investors for a one year reverse convertible bond linked to the price of Google Inc. that was issued by UBS (CUSIP 90268F112). The reverse convertible pays a monthly coupon of 9.25%. If at maturity the price of Google closes above the protection price (convertible trigger price) of \$422.63 (80% of the initial price), investors will receive 100% of the principal at maturity earning a return of 9.25%. If the share price of Google Inc. closes below \$422.63, the issuer will pay the bondholder 1.89 shares of Google Inc. per \$1,000 invested ($\$1,000/\text{Initial Price}$) rather than 100% of the principal amount invested. The above figure displays the final return to investors based on the price of Google Inc. at maturity.

FIGURE A-2: DISPERSION IN RISK ADJUSTED RETURNS

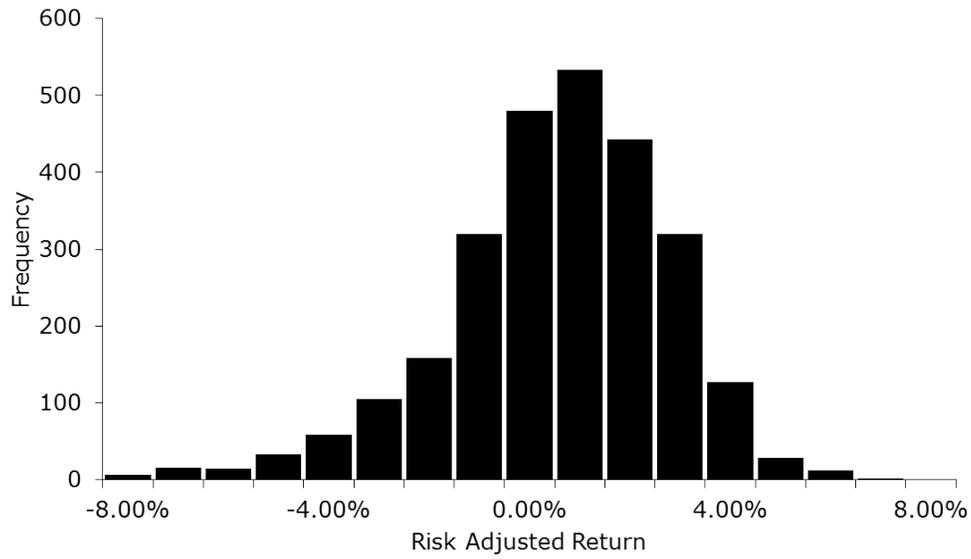


Figure A-2 Notes: The figure displays dispersion in reverse convertible risk-adjusted returns. I calculate the risk adjusted return of each reverse convertible as the present value of coupon payments (assuming monthly coupons discounted using the one year swap rate) minus the implied option premium, the issuer CDS spread and the one year risk free rate (as measured using the one year swap rate). I normalized risk-adjusted returns such that the average return is zero.

TABLE A-1: STRUCTURAL ESTIMATION RESULTS

Variables	(1)	(2)
Coupon (α)	1	1
Option Premium (γ^{Delta})	-0.673***	-1.64***
	(0.10)	(0.25)
Scaling Parameter (θ_1)	72.35*	49.11
	(39.14)	(41.48)
Data Set	All Convertibles	Apple Linked
Observations	1513	189
Number of Markets	498	36

*Table A-1 Notes: Table A-1 displays the structural estimation results using the full data set and restricting the data set to Apple linked reverse convertibles. Standard errors are calculated using the observed Fisher Information Matrix. *, **, *** indicate significance at the 10%, 5% and 1% level.*

FIGURE A-3: SEARCH COSTS

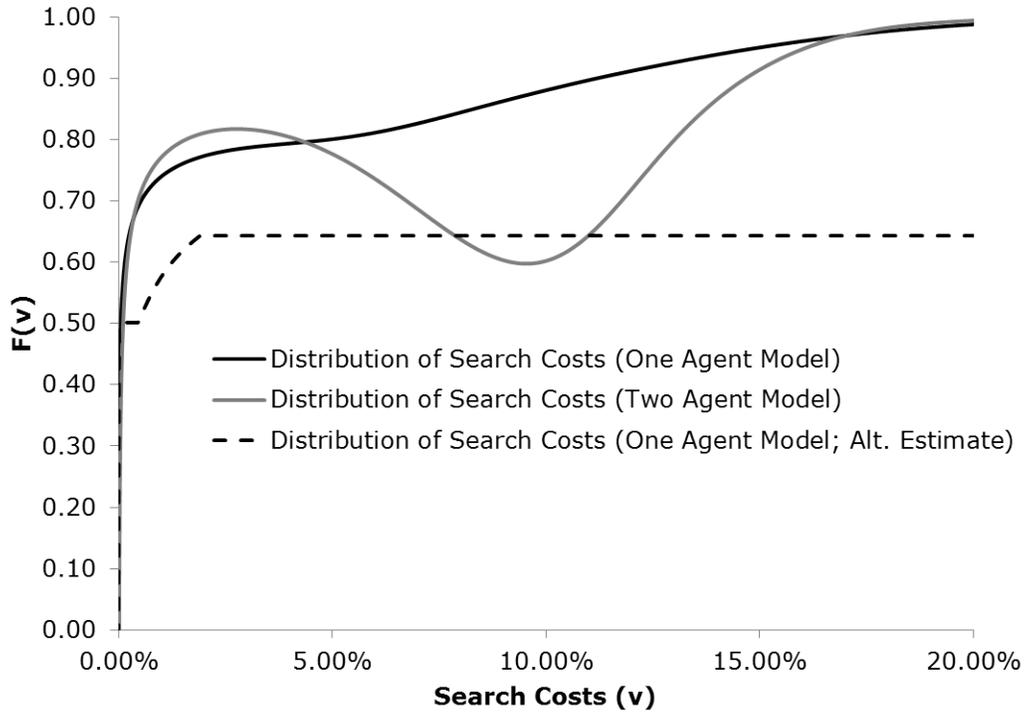


Figure Notes: Figure A-3 displays the estimated distribution of search costs. The baseline specifications correspond to the estimates in columns (1) and (2) of Table 4. The baseline specifications do not force the estimated distribution of search costs to be weakly increasing. The alternative estimation specification forces the estimated distribution of search costs to be positive and weakly increasing by using a B-spline approximation to $G(\cdot)$ with 10 break points. The corresponding parameter estimates in the alternative specification are comparable to those in baseline specifications ($\gamma^{opt} = -1.84$, $\theta_S = 36.45$).