

Too-Systemic-to-Fail: What Option Markets Imply about Sector-Wide Government Guarantees[†]

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We examine the pricing of financial crash insurance during the 2007–2009 financial crisis in US option markets, and we show that a large amount of aggregate tail risk is missing from the cost of financial sector crash insurance during the crisis. The difference in costs between out-of-the-money put options for individual banks and puts on the financial sector index increases four-fold from its precrisis 2003–2007 level. We provide evidence that a collective government guarantee for the financial sector lowers index put prices far more than those of individual banks and explains the increase in the basket-index put spread. (JEL E44, G01, G13, G21, G28, H81)

Investors can purchase out-of-the-money (OTM) put options to insure their positions in the event of a price crash. During the 2007–2009 financial crisis, an episode of elevated systemic risk, the price of crash insurance for the US financial sector as a whole was surprisingly low. Our paper documents that OTM put options for the financial sector stock index were extraordinarily cheap relative to OTM put options on the individual banks that comprise the index. The cost of a basket of individual bank put options exceeded the cost of the index put by 69 percent in March 2009, or by 12.4 cents per dollar of insurance. Between 2003 and 2007, before the onset of the crisis, this basket-index put spread never exceeded 3.3 cents per dollar.

The increase in the basket-index spread in the financial sector during the crisis is puzzling. The basket of put options provides insurance against both sector-wide and idiosyncratic bank stock crashes, while the index put option only insures against a sector-wide crash. Standard option pricing logic therefore implies that a disproportionate increase in idiosyncratic risk (relative to aggregate risk) is needed to explain the dramatic increase in the basket-index put spread during the crisis. This creates a

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puzzle because the correlation of financial stocks also surged throughout the crisis. The drastic rise in idiosyncratic risk necessary to explain the put spread counterfactually implies a sharp decrease in stock return correlations.

We hypothesize that a sector-wide bailout guarantee in the financial sector is largely responsible for the divergence of individual and index put prices during the recent crisis. The anticipation of government intervention during a financial sector collapse lowers the market price of crash insurance for the entire financial sector, but less so for individual banks. In effect, implicit bailout guarantees are crash insurance subsidies for anyone holding stock in the banking sector, and this subsidy drives down the market price that investors are willing to pay for the traded, private version of insurance. Since any individual bank may still fail amid a collective guarantee, or the failure of a single firm may not be sufficient to trigger government intervention, the downward pressure on individual bank puts is much weaker than the effect on index puts.

We provide direct and indirect evidence in favor of this hypothesis. First, we carefully document the rise in the basket-index put spread for the financial sector during the crisis (Section I). We find that no other sector experienced such an abnormal rise in put spreads. We also show that the divergence in basket and index option prices is most pronounced for OTM put options. The OTM call spread remains largely unchanged in all sectors during the crisis.

In Section II, we provide a conceptual framework for interpreting the basket-index spread facts. Spread behavior can be summarized in terms of volatility of the typical stock in the index and in terms of correlation among stocks. Absent a bailout, the basket-index spread falls as correlations rise because stocks are more similar to the index. We also show that spreads can rise when stock volatility increases. However, this volatility effect weakens as the correlation among individual stocks increases and cannot account for the increase in the data. Intuitively, when correlations are very high, the index provides little diversification, so that stock and index volatility move approximately one-for-one. During the crisis, both backward-looking (realized) and forward-looking (implied by call options) correlation measures increased sharply in the financial sector. Realized and call-implied correlations reached maxima of 84 percent and 93 percent in September and November 2008, respectively, far exceeding correlations in other sectors.¹

We show that these two facts, the simultaneous increase in financial sector correlations and the financial sector basket-index put spread, are not only conceptually puzzling, but are *quantitatively* at odds with standard asset pricing models (Section III). Canonical models suggest that the rapid increase in return correlations would have contributed to a rapid rise in the price of OTM index options relative to the basket.

To demonstrate this point, we theoretically derive joint pricing formulas for options on a sector index and individual stocks in a model that incorporates both common and idiosyncratic Gaussian and non-Gaussian shocks.

¹Meanwhile, put implied correlation falls in the financial sector during the crisis, diverging from the behavior of calls and the behavior of the underlying returns themselves. This is another manifestation of the puzzling put basket-index spread for financials, as implied correlations are derived from a comparison of prices for index options and individual stock options.

In its simplest form, our model reduces to the well-known Black-Scholes model (Black and Scholes 1973; Merton 1973), which we develop as a special case to help convey the intuition of our approach. The Black-Scholes model directly maps time-series fluctuations in the underlying index and individual stock volatilities into option prices without requiring estimation of parameters. We show that the Black-Scholes model cannot explain the financial sector basket-index put spread dynamics even after taking into account rising volatilities and correlations among financial stocks. In contrast, the Black-Scholes model successfully matches put spread dynamics for nonfinancial sectors both before and during the crisis.

A shortcoming of Black-Scholes is that it fails to capture the high *levels* of OTM index option prices. We therefore allow for sector-wide and stock-specific price jump risk following Merton (1976). The Merton jump model explains precrisis basket and index put price levels much better than the Black-Scholes model in *all* sectors. However, this more sophisticated option pricing model still fails to explain the large basket-index spread among financials during the crisis.

The Merton jump model also allows us to address a leading alternative explanation for the drastic change in spreads during the crisis, namely that investors become more risk averse during the crisis. Because risk aversion only interacts with aggregate shocks, a rise in risk aversion drives up the price of insurance against aggregate risks and leaves the price of insurance against idiosyncratic risks unchanged. All else equal, this leads to a *decline* in the basket-index spread. Hence, a rise in risk aversion exacerbates the puzzle of high crisis spreads in the financial sector rather than resolving it.

We then ask whether a financial sector-wide bailout guarantee can help explain the puzzling behavior of financial sector put prices (Section IV). We model the bailout as a cap on the losses that can be experienced by the aggregate financial sector equity portfolio and we derive closed-form expressions for option prices. By capping losses, the government endows all investors in the financial sector equity index with a free, deep OTM put option. Our main result is that embedding a bailout in the Merton jump model reconciles the observed financial sector option prices with the realized volatility and correlation dynamics before and during the financial crisis. The bailout model accurately matches the put spread while remaining consistent with call prices and the high overall level of put prices. This analysis provides indirect evidence that a government guarantee can account for dynamics of the basket-index put spread over this period.

To quantify the implicit subsidy that the government gives to financial sector equity holders, we use the calibrated Merton jump model as a laboratory to study the counterfactual: what would the price of crash insurance have been had the government not provided a bailout guarantee? We compare the price of put options in the estimated bailout model to the cost in an otherwise identical economy where the bailout is set to zero. During the crisis, we find that the guarantee lowers the insurance premium for financial index crash insurance by 73 percent on average. In dollar terms, option prices imply an average subsidy to equity holders of \$282 billion during our sample. These numbers are admittedly approximations and are dependent on model specification assumptions. They nonetheless indicate a substantial reduction in the cost of equity capital for systemically risky financial firms.

To provide direct evidence of option price sensitivity to bailout guarantees, we conduct an event study around key government announcements during the crisis (Section V). The financial sector basket-index put spread increases on average by 31 percent in the first five days after those government announcements that ex ante increases the probability of a government bailout. The put spread decreased on average by 38 percent after announcements that have the opposite effect. Both of these calculations adjust for changes in financial sector risk via the Merton jump model, and difference out the effects in nonfinancial sectors.

We also use the tech crash as a placebo test for our measure of sector-wide bailouts. From 2000 to 2002, the technology sector index experienced a crash of the same magnitude as the finance sector crash in 2007 to 2009. We find that, unlike the financial sector spread during the recent crisis, there is no evidence of a divergence between risk-adjusted basket and index put prices for the technology sector during this episode. The *absence* of a large put spread in tech sector collapse supports our bailout interpretation of financial sector option market behavior during the recent crisis.

While our emphasis is on collective or “too-systemic-to-fail” guarantees, some financial institutions may benefit more than others. We document differences in put prices and credit default swap rates across banks. Risk-adjusted crash insurance prices for large banks are lower than those of their smaller peers, indicating investors perceive differences in bailout likelihoods across institutions consistent with an implicit “too-big-to-fail” guarantee.

Finally, we explore a number of additional alternative explanations for the increase in the basket-index put spread in Section VI. Transaction costs can be ruled out because the basket-index put spread constructed with the most costly combination of bid and ask quotes is still large. Liquidity differences across various types of options (index versus individual, puts versus calls, or financial firms versus non-financials), are inconsistent with the put spread arising due to illiquidity. Mispricing due to capital constraints, counterparty risk, and short sale restrictions are unlikely culprits. A trade that takes advantage of the basket-index spread ties up relatively little capital (due to implicit leverage in options) and occurs through exchanges with a clearing house. These option positions are marked-to-market daily and ultimately guaranteed by the AAA-rated Options Clearing Corporation. The short sale ban was in place only for a brief portion of the financial crisis, applied equally to individual and index options, and market makers were exempted from it. Nor do short sale lending fees for financial stocks line up with the put spread dynamics that we document.

Our work connects to various strands of the literature. First, it is linked to the problem of measuring systemic risk in the financial sector, one of the major challenges confronting financial and macro-economists.² Our findings highlight a fundamental complication in inferring systemic risk from market prices. In the presence of an implicit or explicit guarantee, insurance prices may *fall* when the guarantee is more likely to be activated. This fall could be mistakenly interpreted as drop in risk exactly at the time that systemic risk is rising. Thus, anticipation of future

²See Acharya et al. (2010); Adrian and Brunnermeier (2010); Brownlees and Engle (2010); and Huang, Zhou, and Zhu (2011) for recent advances in systemic risk measurement, and Brunnermeier et al. (2010) for an overview of related research challenges.

government intervention is embedded in market prices, which clouds their informativeness regarding true underlying tail risk.³

The effects of too-systemic-to-fail government guarantees are an active topic of investigation.⁴ Veronesi and Zingales (2010) use credit default swap (CDS) data to measure the value of government bailouts to bondholders and stockholders of the largest financial firms from the 2008 Paulson plan. Their focus on credit contracts is consistent with the prevailing notion that bailouts rescue debt holders at the expense of equity holders. We test the hypothesis that collective government guarantees to the financial sector benefit bank equity holders. Creditor bailout guarantees can benefit shareholders due to uncertainty about the resolution regime (especially for large financial institutions) and because bankruptcy costs may start well before the value of bank equity hits zero.⁵ We document that government guarantees pledged substantial value to financial sector equity holders during this crisis, even if the guarantee intended to target debt holders. This finding is useful for understanding potentially unintended consequences of a collective guarantee for the financial system.⁶

I. Measuring the Basket-Index Spread

Equity options are especially well suited as a gauge of the market's perception of too-systemic-to-fail guarantees. Puts pay the owner of the option \$1 for each dollar that the underlying equity falls below a contracted threshold. One may insure against a financial sector crash by buying puts: On each individual financial institution that is part of the index, or on the financial sector index itself. This paper compares of the cost of these two insurance schemes with the goal of learning about investor perceptions of bailouts.

We focus on a sector index comprised of N different stocks. To insure the downside risk using puts on individual stocks, we consider a basket of options that matches the sector index composition on each day. Let w_j be the number of shares outstanding, respectively, for stock j in the index. Denoting the price of a put option as P , the dollar cost of the basket is the sum of individual stock puts necessary to insure each share in the index, and is given by

$$(1) \quad P^{basket} = \sum_{j=1}^N w_j P_j.$$

Alternatively, one can insure the sector portfolio directly by buying put options on the sector index, at a price of P^{index} .

³The feedback from anticipated corrective action to market prices echoes the problem of a board of directors monitoring share prices to fire a CEO (Bond, Goldstein, and Prescott 2010).

⁴A number of papers measure the impact of these guarantees, starting with the seminal work of Merton (1977) on deposit insurance. Lucas and McDonald (2006, 2010) take an option-based approach to valuing guarantees extended to Fannie Mae and Freddie Mac.

⁵O'Hara and Shaw (1990) estimate large positive wealth effects for shareholders of banks who were declared too-big-to-fail by the Comptroller of the Currency in 1984, and negative wealth effects for those banks that were not included. Also see Kareken and Wallace (1978) and Panageas (2010).

⁶Our paper is also related to recent studies of the relative pricing of derivative securities. Coval, Jurek, and Stafford (2009) and Collin-Dufresne, Goldstein, and Yang (2012) compare the prices of credit default index (CDX) tranches to those of index options prior to and during the financial crisis, while Driessen, Maenhout, and Vilkov (2009); Carr and Wu (2009); and Schürhoff and Ziegler (2011) study prices of index versus individual options prior to the crisis.

The basket of put options provides insurance against both common and idiosyncratic stock price crashes, while the index put option only insures states of the world with a common crash. The difference between the costs of these insurance schemes is informative about the relative importance of aggregate and idiosyncratic risks.

A. Basket-Index Option Price Spreads

To align our cost comparison, we equalize the insured value of sector equity in each insurance scheme by matching strike prices. We first choose the OTM index option with strike price K_t^{index} and Black-Scholes delta of 25 in absolute value.⁷ The Black-Scholes delta approximates the percentage probability that the option owner receives a positive payout.

Next, we identify the set of options on individual stocks in the index that share the same delta and whose combined strike prices K_j satisfy $K^{index} = \sum_{j=1}^N w_j K_j$. That is, the strike price of the index equals the share-weighted sum of the individual strike prices, just as the sector index market capitalization is a share-weighted sum of stock prices. The delta of all individual stocks is required to be the same, though this can differ from the index delta. Typically the stock delta is slightly higher than the index delta because the stock volatility exceeds index volatility, which increases the probability of the stock option payoff for a fixed strike price.

Our use of strike-matching is motivated by Merton (1973), who shows that the cost of the basket of put options invariably exceeds the cost of the index option in the absence of arbitrage opportunities. This follows from option payoffs at maturity satisfying the following inequality:

$$(2) \quad \sum_{j=1}^N w_j \max(K_j - S_j, 0) \geq \max\left(K^{index} - \sum_{j=1}^N w_j S_j, 0\right),$$

where S_j is the value of the underlying stock at maturity. Because the payoff from the option basket exceeds that of the index option, its cost must be weakly higher as well. This bounds the basket-index spread from below at zero.

To compare prices across time, sectors, and between puts and calls, we define the *cost per dollar insured* as the price of an option position divided by the equity dollar value that it guarantees. We then define a sector's *basket-index put spread* as the difference in the per dollar costs of basket and index insurance

$$(3) \quad \text{Put Spread} = \frac{P^{basket} - P^{index}}{K^{index}}.$$

We define call spreads analogously. We build call and put spread in all sectors for each day in our sample.⁸

⁷When we quote put option deltas as positive numbers we are referring to the absolute value. In online Appendix J we report option prices for a range of deltas.

⁸Online Appendix A reports option spread results when the basket and index are chosen to have the same option delta, rather than the same strike price. The results are qualitatively identical to strike-matched results. We also compare index and basket put prices using options positions that share the same sensitivity to changes in stock return volatility, the so-called option "vega." When we take the vega-matched approach, spreads between index and basket

B. Data

We use daily options data from January 1, 2003 to June 30, 2009. This includes options on nine S&P 500 sector index exchange-traded funds (ETF) and options on each stock in the S&P 500, all of which are traded on the Chicago Board of Exchange (CBOE). The nine sector ETFs have no overlap and collectively span the entire S&P 500. Online Appendix B contains more details and lists the top 40 holdings in the financial sector ETF.⁹

The OptionMetrics Volatility Surface file provides daily standardized implied volatilities for put and call options that have been interpolated over a grid of time to maturity and option delta. These constant maturity and constant moneyness options are available at various intervals between 30 and 730 days to maturity and at values of (absolute) delta ranging from 20 to 80. We focus primarily on options with 365 days to maturity and delta of 25.¹⁰

ETF options share the same contractual features as individual stock options, including their American exercise feature. OptionMetrics reports an equivalent European option implied volatility that accounts for the American option feature of the raw data. This implied volatility can be used with the Black-Scholes European option formula to construct option prices that are appropriate for analysis with canonical option pricing models (whose formulas are typically applicable only to European options). All of our analysis uses these European option prices. A similar approach is used in Christoffersen, Fournier, and Jacobs (2015), who also study US options on individual stocks.

We use Center for Research in Security Prices (CRSP) for data on prices, returns, and number of shares outstanding for sector ETFs and individual stocks. We calculate the realized volatility of index and individual stock returns, as well as realized correlations among stocks in each sector. Our calculations exactly track the varying composition of the S&P 500 index (as well as the sector indices) to maintain consistency between the basket and the index each day.

C. The Rise of Financial Sector Put Spreads

Table 1 reports summary statistics for basket-index put and call spreads in cents per dollar insured. The first two columns report spread statistics for the financial sector in the precrisis sample (January 2003 to July 2007) and crisis sample (August 2007 to June 2009). Columns three and four are equity value-weighted averages of the eight remaining nonfinancial sectors. We also show differences in spreads for

put prices widen even more for financials versus nonfinancials compared to the strike-matched results reported below. Detailed estimates from our vega-matched put price comparison are available upon request.

⁹Our sample length is constrained by the availability of ETF option data. For the financial sector (but not for all nonfinancial sectors), we are able to go back to January 1999. The properties of our main object of interest, the basket-index put spread for financials, are unchanged if we start in 1999.

¹⁰To ensure that our facts regarding basket-index put spreads are not driven by widening bid-ask spreads during the financial crisis, we reconstruct an alternative basket-index spread series using raw option price quotes rather than the interpolated volatility surface provided by OptionMetrics. This also serves as a check that OptionMetrics interpolated prices do not suffer from inaccurate extrapolation or reliance on illiquid contracts. We explore this robustness check in detail in online Appendix C. Results from raw options data, combined with accounting for bid-ask spreads and contract liquidity, generates put spreads that are qualitatively identical, and quantitatively very similar, to the results we report above.

TABLE 1—BASKET-INDEX SPREADS

		Financials		Nonfinancials		Financials – Nonfinancials		
		Puts	Calls	Puts	Calls	Puts	Calls	Puts – Calls
Precrisis	Mean	1.4	1.6	2.4	2.4	-1.0	-0.8	-0.2
	Std	0.3	0.2	0.6	0.2	0.4	0.3	0.5
	Max	3.3	2.4	4.6	3.1	0.2	-0.1	0.9
Crisis	Mean	4.6	2.1	3.3	2.9	1.3	-0.8	2.0
	Std	2.5	0.5	0.9	0.5	2.0	0.5	2.0
	Max	12.4	3.5	6.3	4.2	7.9	0.6	10.0

Notes: Summary statistics of daily basket-index put and call spreads for the financial sector, nonfinancial sectors, and their difference. The final column reports the difference-in-differences (financials minus nonfinancials, puts minus calls). Units are cents per dollar insured. The pre-crisis sample is January 2003 to July 2007 and the crisis sample is August 2007 to June 2009. Index delta is fixed at 25 and time to maturity is 365 days.

financials versus nonfinancials and the difference-in-differences for puts versus calls in the final two columns. An increase in the spread between the basket and the index means index options become cheaper relative to the individual options.

Over the precrisis sample, the mean put spread is 1.4 cents per dollar insured in the financial sector, and 2.4 cents in the nonfinancial sectors. During the financial crisis, the mean put spread is 4.6 cents per dollar for financials and 3.3 cents for nonfinancials. While there is an across-the-board increase in the put spread from the precrisis to the crisis periods, the increase is much more pronounced for financials (3.3 times, versus 1.4 times for nonfinancials). The largest basket-index put spread for financials is 12.4 cents per dollar, recorded on March 9, 2009. It represents 69 percent of the cost of the index option on that day. On that same day, the difference between the spread for financials and nonfinancials peaks at 7.9 cents per dollar insured. Prior to the crisis, the put spread for financials never exceeds 3.3 cents on the dollar, and it never exceeds the nonfinancial put spread by more than 0.2 cents.

Across the entire sample, the nonfinancial spreads for puts and calls are similar. Precrisis nonfinancial put and call spreads are identical at 2.4 cents, while during the crisis the put spread rises slightly above calls (3.3 versus 2.9 cents). In contrast, the financial sector put spread is smaller than the call spread precrisis (1.4 versus 1.6), but during the crisis the put spread is on average 220 percent larger than the call spread (4.6 versus 2.1). The difference in financial sector put and call spread peaks at 10.8 cents. For nonfinancials, this difference never exceeds 2.3 cents.

Panel A of Figure 1 plots financial sector put prices for the entire sample. The dotted gray line shows the cost of the basket of put options per dollar insured and the solid gray line plots the cost of the financial sector put index. Before the financial crisis, the basket-index put spread (black line) is small and essentially constant at around 1 cent per dollar. During the crisis, the spread widens dramatically as index options fail to keep pace with the rise in the cost of the basket. The basket cost exceeds 30 cents per dollar in March 2009, while the cost of the index put rarely exceeds 20 cents.

Panel B plots financial sector call option prices and the call spread. During the crisis, the difference between index calls and the call basket remains close to its precrisis level, and never exceeds 3.5 cents. Panels A and B have different scales, as call costs never exceed 9 cents.

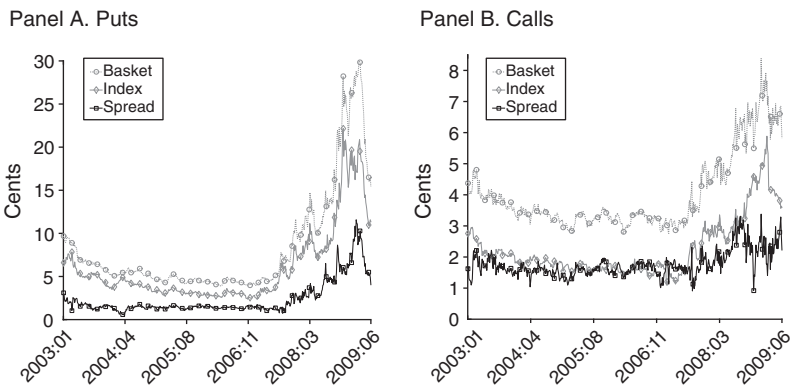


FIGURE 1. COST OF INSURING FINANCIAL SECTOR EQUITY

Notes: The cost of financial sector insurance based on options on the index (solid gray line) and options on the basket (dotted gray line), as well as the basket-index spread (black line). Units are cents per dollar insured. Delta is 25 and time to maturity is 365 days. Panel A uses put options and panel B uses call options.

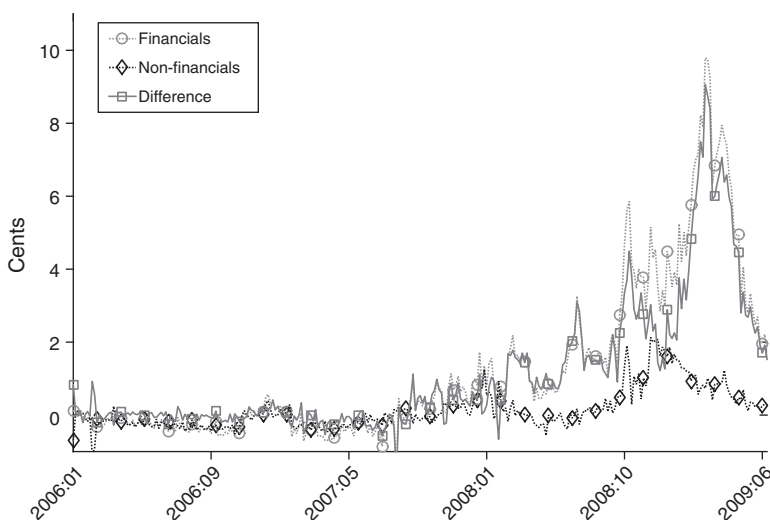


FIGURE 2. BASKET-INDEX SPREAD (*Puts Minus Calls*) ACROSS SECTORS

Notes: Basket-index spreads (puts minus calls) for the financial sector (marked by circles), the nonfinancial sector (marked by diamonds), and their difference (financials minus nonfinancials, marked by squares). Units are cents per dollar insured. Delta is 25 and time to maturity is 365 days.

Figure 2 compares the difference in basket-index spreads (puts minus calls) for the financial sector (marked by circles), nonfinancial sector (marked by diamonds), and the difference-in-differences (financials minus nonfinancials, marked by squares). The financial spread begins widening in August 2007 (the asset-backed commercial paper crisis), spikes in March 2008 (the collapse of Bear Stearns), and then spikes further after the bailouts of Freddie Mac and Fannie Mae and the Lehman Brothers bankruptcy in September 2008. After a brief decline at the end of 2008, the spread

peaks a second time with the rescue of AIG in March 2009. The nonfinancials spread remains low until October 2008, when it experiences a small rise. This difference between sectors is slightly negative precrisis, indicating that financial sector index options (compared to the cost of the basket) were relatively more expensive than their nonfinancial counterparts. It switches to large and positive at the August 2007 onset of the crisis, then rises sharply to its March 2009 peak, indicating that financial sector crash insurance became increasingly underpriced throughout the crisis.

We argue that an implicit government guarantee to the financial sector is responsible for the stark rise in financial put spreads. To provide a foundation for interpreting the empirical facts, we first describe the theoretical determinants of basket-index spreads through the lens of canonical option pricing models. When we quantitatively assess these models' ability to match patterns in the data, we conclude that the models are incapable of producing the patterns above in option prices. Finally, we demonstrate that the data are consistent with an augmented model that includes a bailout guarantee.

II. The Determinants of Basket-Index Spreads

We analyze the structure of option spreads in two canonical pricing models. The first is the Black-Scholes (BS) model, whose Gaussian setting is especially transparent for understanding insurance prices because spreads are determined by only two quantities: the return volatility of stocks in the index and the degree of return correlation among those stocks. Then, to understand the role of deviations from normality, we study spreads in the Merton jump (MJ) model. While the determinants of spreads are conceptually the same in both settings, the presence of jump risk in the MJ model is essential for matching the high levels of put prices observed in the data.

A. Spreads in the Black-Scholes Model

We study a one-factor discrete time version of the BS model. The log annual return on an individual stock is governed by the following distribution:

$$(4) \quad r_s = \mu + \sqrt{\rho} \epsilon_x + (\sqrt{1 - \rho}) \epsilon_s,$$

where ϵ_x is an i.i.d. sector-wide index shock distributed $N(0, \sigma^2)$ and ρ is nonnegative. Branger and Schlag (2004) study index option prices under a similar factor structure. The stock-specific shock, ϵ_s , is also $N(0, \sigma^2)$ and is i.i.d. over time and across firms. Thus, the stock's return volatility is σ and is independent of the level of between-stock correlation, ρ . The expected return on the stock is μ , which is the sum of the expected return on the index, μ_x , and an idiosyncratic volatility adjustment. The log return on the index is $r_x = \sum_s w_s r_s$. For nondegenerate index weights w_s , the index return and its variance have limiting behavior of

$$r_x \rightarrow \mu_x + \sqrt{\rho} \epsilon_x, \quad V(r_x) \rightarrow \rho \sigma^2$$

as the number of stocks becomes large. For expositional ease we assume that the index is composed of enough stocks that these limits hold with equality. Our analysis

in online Appendix D demonstrates that our findings are essentially unchanged when we carefully account for heterogeneity in index weights and risk across stocks in the basket.

The factor structure in (4) allows us to simultaneously consider pricing of options on an individual stock and options on the index. Since we are interested in European option prices on one-year contracts, we simply model annual returns. The price of a put option on an individual stock is given by the BS formula, denoted $P^{BS}(\sigma, S_0, K, r)$, where the stock price is S_0 , the strike price is K , the annual interest rate is r , and the option matures in one year. Normalizing the index price to equal the stock price, and choosing stock and index options that are strike and maturity matched, the index put price is $P^{BS}(\sqrt{\rho}\sigma, S_0, K, r)$. For exposition, we assume symmetry among individual stocks so that the basket of individual stock puts is identical to any single put. And we suppress the dependence of prices on S_0, K , and r , all of which are held fixed throughout and are the same for the index and the basket.¹¹

This formulation implies that the strike-matched basket-index put spread is

$$(5) \quad \text{Put Spread}^{BS} = P^{BS}(\sigma) - P^{BS}(\sqrt{\rho}\sigma).$$

This simple formula reveals that the spread is determined solely by two features of individual stock returns: their own volatility σ and their correlation ρ with other stocks in the index. In this setting, spreads can be characterized by the sensitivity of option prices to equity volatility. We define this derivative as $\nu(\tilde{\sigma}) \equiv \partial P(\tilde{\sigma})/\partial \tilde{\sigma}$, commonly referred to as option “vega.” In the BS setting, it takes the form¹²

$$(6) \quad \nu^{BS}(\tilde{\sigma}) \propto \exp\left\{-\left(\log \frac{S_0}{K} + \left(r + \frac{\tilde{\sigma}^2}{2}\right)T\right)^2\right\}.$$

Spread behavior is summarized by three facts. First, as the correlation among stocks rises, the basket-index spread falls,

$$(7) \quad \frac{\partial \text{Put Spread}^{BS}}{\partial \rho} = -\nu(\sqrt{\rho}\sigma) \frac{\sigma}{2\sqrt{\rho}} \leq 0.$$

This follows directly from the nonnegativity of (6). A rise in correlation means that all stocks have become more similar to the index. The index is therefore less diversified and more volatile, though individual stock volatility has not changed. Put prices are strictly increasing in volatility, therefore the price of the index option rises, pushing down the basket-index spread. When correlation is maximized, the basket and index are identical and the spread drops to zero. Panel A of Figure 3 illustrates the sensitivity of basket-index spreads to correlation, holding volatility fixed.

¹¹ By the homogeneity of the BS formula in K and S_0 , prices in cents per dollar insured may be rewritten $(1/K)P^{BS}(\sigma, S_0, K, r) = P^{BS}(\sigma, S_0/K, 1, r)$, where S_0/K describes the option’s “moneyness.” Our strike-matched construction of spreads fixes S_0/K for the basket and index. In the empirical analysis, r is determined by data and varies over time, though this variation is a comparatively small determinant of variation in spreads.

¹² We use $\tilde{\sigma}$ to note that the derivative is with respect to the underlying equity volatility, which differs for the stock and the index. In particular, $\tilde{\sigma} = \sqrt{\rho}\sigma$ for the index.

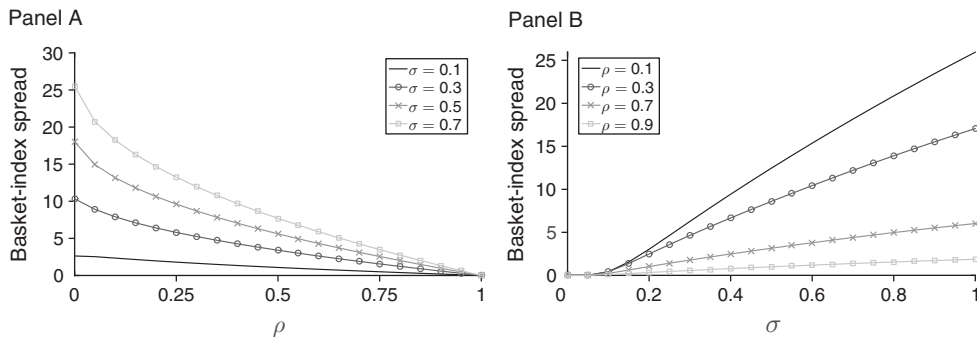


FIGURE 3. BASKET-INDEX SPREAD COMPARATIVE STATICS: BS MODEL

Notes: Basket-index put spreads in the BS model across parameter values. Spot price is 1, strike price is 0.9, risk-free rate is 3 percent, and maturity is 1 year. Units are cents per dollar insured.

Second, as stock volatility increases, the basket-index spread rises. This derivative is equal to a difference in vegas:

$$(8) \quad \frac{\partial Put Spread^{BS}}{\partial \sigma} = \nu(\sigma) - \nu(\sqrt{\rho} \sigma) \sqrt{\rho} \geq 0.$$

From (6), it is immediate that the ratio $\frac{\nu(\sigma)}{\nu(\sqrt{\rho} \sigma) \sqrt{\rho}}$ is never less than 1. So, a rise in σ always increases the basket’s option price by more than the index, driving up the basket-index spread. This is because a rise in σ corresponds to a one-for-one rise in individual stock volatility, while the effect of σ on index volatility is muted by the factor $\sqrt{\rho}$. Panel B in Figure 3 shows the effect of volatility on spreads, holding correlation fixed.

Third, the basket-index spread is less sensitive to volatility at higher levels of correlation for OTM options. When correlation is high, an increase in stock volatility has relatively little impact on the basket-index spread because stock and index volatility both move nearly one-for-one with σ . As the correlation tends to one the basket and index are all but identical, thus volatility has no impact on the spread.¹³

Financial crises are characterized by extreme levels of both volatility and correlation. The figure demonstrates that it is exactly during episodes of elevated ρ and σ that the spread becomes primarily dependent on correlation, and is less sensitive to volatility. This is a first indication that, due to the high return correlations among banks during the crisis, the sharp rise in financial sector spreads observed during the crisis may be inconsistent with the benchmark BS model, a point that we quantitatively investigate in detail below.

¹³For OTM options such as those we study, $\partial^2 Put Spread^{BS} / \partial \sigma \partial \rho$ is negative. Formally, the sign of $\partial^2 Put Spread^{BS} / \partial \sigma \partial \rho$ depends inversely on the product

$$\left[\log(S_0/K) + (r + \sigma^2/2) T \right] \left[\log(S_0/K) + (r - \sigma^2/2) T \right],$$

whose value is determined by the option’s moneyness. For deep OTM options this product is unambiguously positive.

B. Spreads in the Merton Jump Model

The BS model assumes that log price changes are normally distributed. Many extensions of BS find that deviations from normality, typically through infrequent price jumps or stochastic volatility, improve the model's ability to fit options data. To analyze how spreads behave in the presence of nonnormalities, we construct a one-factor, discrete-time version of Merton's (1976) jump model. The same qualitative associations between volatility, correlation, and the basket-index spread that we described in the BS setting also arise in the richer setting of non-Gaussian returns. In particular, the correlation among stocks, not their volatility, is the dominant determinant of the basket-index spread during the crisis.¹⁴

Under the physical measure, the annual log stock return for an individual stock in our MJ model evolves according to

$$(9) \quad r_s = \mu + \sqrt{\rho} \epsilon_x + \sqrt{1 - \rho} \epsilon_s + J_x + J_s.$$

As in BS, ϵ are independent normals with distribution $N(0, \sigma^2)$ and ρ governs the correlation of Gaussian components. We allow for jumps that fatten the tails of returns relative to the normal distribution. The aggregate jump, J_x , is common to all stocks in the index and follows a Poisson-normal mixture distribution. That is, with probability $e^{-\omega_x} \omega_x^j / j!$ the jump will be drawn from the distribution $N(j\theta, j\delta^2)$, for $j = 0, 1, 2, \dots$. The "intensity" of jump arrivals is ω_x and the mean and variance of jump sizes are θ and δ^2 . The variance of this type of jump shock is $V(J_x) = \omega_x(\delta^2 + \theta^2)$. We also allow for independent stock-specific jumps, J_s , that are distributed Poisson-normal as well.

We assume that the correlation among jump shocks is identical to the correlation among Gaussian shocks. We also assume that the variance of jumps is proportional to the variance of Gaussian shocks. Both of these are controlled via arrival intensities. In particular, we set the intensity of J_x to $\omega_x = \rho\sigma^2\omega$, and the intensity of J_s to $(1 - \rho)\sigma^2\omega$.¹⁵ This implies that the total jump intensity for an individual stock in the basket is $\sigma^2\omega$, and the intensity for the index is $\rho\sigma^2\omega$ in the limit of many stocks. Finally, we assume that the jump size parameters θ and δ^2 are identical for aggregate and idiosyncratic jumps. Each of these restrictions reduces the number of parameters to improve the model's parsimony, but relaxing the restrictions does not change the main results or conclusions.

¹⁴An alternative device for modeling nonnormalities is stochastic return volatility. We focus on nonnormalities in the form of jumps for two reasons. The first is analytical convenience. Second, Backus, Chernov, and Martin (2011) argue that the moneyness structure of options, or "smile," is well-matched by jump risk alone, while stochastic volatility is an important feature for matching the maturity structure of option prices. Our research question requires a comparison of option prices across moneyness (OTM puts versus OTM calls) as opposed to maturity, thus jumps are sufficient for our purposes. A previous draft of this article included a stochastic volatility component in the model, and our empirical findings were qualitatively identical (these results are available upon request).

¹⁵The jump correlation ρ can be equivalently interpreted as the fraction of jumps that are common to all stocks in the index.

As before, we assume the index return is exactly described by its limit as the number of stocks tends to infinity,¹⁶

$$(10) \quad r_x = \mu_x + \sqrt{\rho} \epsilon_x + J_x,$$

thus the total variances of the stock and the index are

$$(11) \quad V(r_s) = \sigma^2(1 + \omega[\delta^2 + \theta^2]), \quad V(r_x) = \rho V(r_s).$$

In our specification, σ governs the overall level of variance in the system, which is contributed by both the Gaussian and jump components of returns. The correlation parameter, ρ , governs the fraction of risk that is common among stocks, and is driven in equal parts by the Gaussian correlation and jump correlation. The intensity parameter, ω , governs the fraction of total variance arising due to jump shocks: When ω goes to zero, all risk is Gaussian and we recover the BS model. Finally, θ and δ govern the extent of nonnormality in returns. Along with ω , they both directly map into the skewness and kurtosis of the return distribution, which generally deviate from their Gaussian counterparts of zero and three, respectively.

In addition to allowing for nonnormalities, an attractive feature of the MJ setting is that it explicitly allows basket-index spreads to depend on risk premia, a consideration that is absent from BS. The distributions of log returns corresponding to (9) are specified under the physical, or “real world” probability measure. Pricing assets in the MJ model also requires modeling investor preferences. We assume a representative agent with constant relative risk aversion (CRRA) preferences over market wealth and nonnegative risk aversion α . To understand option prices in the MJ model, it is convenient to construct a “risk-neutral” probability measure that scales physical probabilities by investors’ marginal utility state by state. The mapping from physical to risk-neutral distributions is straightforward in the CRRA case. Throughout, we use an asterisk to denote a parameter of the risk-neutral measure. The transformed parameters of the aggregate jump distribution are

$$(12) \quad \omega_x^* = \omega_x \exp(-\alpha\theta + \alpha^2\delta^2/2), \quad \theta^* = \theta - \alpha\delta^2, \quad \delta^* = \delta.$$

The distribution of idiosyncratic jumps is the same under the physical and risk-neutral measures because these are, by definition, diversifiable and therefore do not command a risk premium. Nor is there an option price premium for aggregate Gaussian shocks since these are hedgeable, as in the BS setting. The derivation of (12), which is based on Backus, Chernov, and Martin (2011), is in online Appendix E.

We denote the price of a put option in the MJ model as P^{MJ} . A convenient feature of this model is that P^{MJ} is known in closed form (given in online Appendix E). The index option price depends only on the risk-neutral index parameters $\Theta_{\mathbf{x}}^* = (\sigma_{\mathbf{x}}, \omega_{\mathbf{x}}^*, \theta^*, \delta)$, where $\sigma_{\mathbf{x}} = \sqrt{\rho} \sigma$. The individual stock option price

¹⁶The intercept, μ_x , includes the risk free rate, the equity risk premium, a volatility adjustment for the Gaussian shock ϵ_x , and a compensator for the fact that J_x may have nonzero mean. The intercept of the stock return, μ , may be written as $\mu_x + \mu_s$, where μ_s includes a volatility adjustment for ϵ_s and a compensator for the idiosyncratic jump, J_s . Explicit formulae for μ_x and μ_s are derived in online Appendix E.

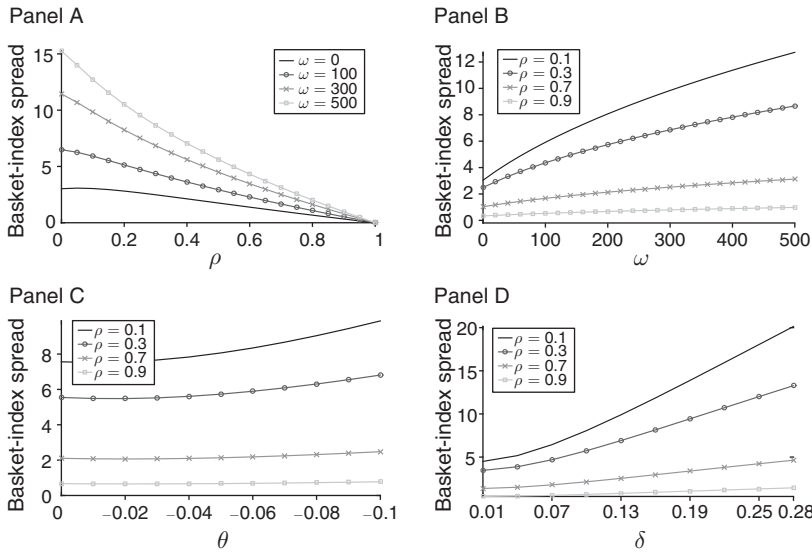


FIGURE 4. BASKET-INDEX SPREAD COMPARATIVE STATICS: MJ MODEL

Notes: Basket-index put spreads in the MJ model. Baseline parameter values are $(\sigma, \rho, \omega, \theta, \delta, \alpha) = (0.2, 0.5, 200, -0.05, 0.1, 1)$ unless otherwise varied in the figure. Spot price is 1, strike price is 0.9, risk-free rate is 3 percent, and maturity is 1 year. Units are cents per dollar insured.

depends on the index parameters and also the idiosyncratic Gaussian and jump shock parameters, $\Theta_s = (\sigma_s, \omega_s, \theta, \delta)$, with $\sigma_s = \sqrt{1 - \rho} \sigma$ and $\omega_s = (1 - \rho) \sigma^2 \omega$. Thus, the MJ basket-index spread is

$$(13) \quad \text{Put Spread}^{MJ} = P^{MJ}(\Theta_x^*, \Theta_s) - P^{MJ}(\Theta_x^*, \mathbf{0}).$$

Figure 4 illustrates the sensitivity of MJ put spreads with respect to non-Gaussian variance and correlation. Panel A shows that a rise in jump correlation decreases the spread, and the decline is sharpest when jump risk is most prevalent (i.e., when the intensity of jump arrivals is high). The remaining panels show that a rise in any of the determinants of jump variance (ω, θ, δ) leads to rise in spreads (more negative θ corresponds to higher risk). However, this effect is muted when jump correlation is high.

In summary, the qualitative effects of variance and correlation on spreads are nearly identical in the MJ and BS models: In times of crisis, the basket-index spread becomes most influenced by jump correlation and is less sensitive to jump variance. This suggests that the sharp rise in financial sector spreads observed during the crisis, which appears inconsistent with the BS model, is unlikely to be explained by nonnormalities in returns.

C. The Role of Risk Premia

The wedges between ω^* and ω and between θ^* and θ summarize the effects of risk aversion on option prices. Both wedges are increasing in α and capture the

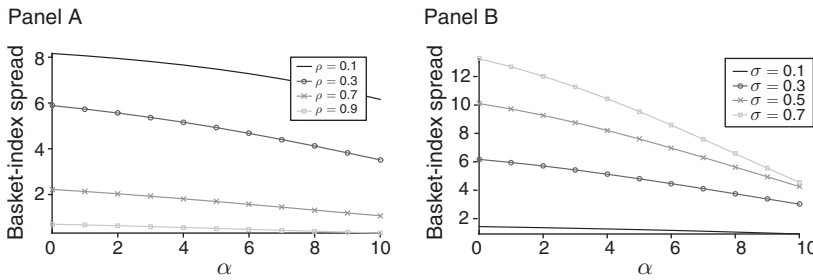


FIGURE 5. RISK AVERSION AND THE BASKET-INDEX SPREAD

Notes: Basket-index put spreads in the MJ model. Baseline parameter values are $(\sigma, \rho, \omega, \theta, \delta) = (0.2, 0.5, 200, -0.05, 0.1)$ unless otherwise varied in the figure. Spot price is 1, strike price is 0.9, risk-free rate is 3 percent, and maturity is 1 year. Units are cents per dollar insured.

intuition of the risk-neutral transformation. The more risk averse investors become, the more weight they place on downside aggregate outcomes when valuing assets: jumps arrive more frequently and the mean jump size is more negative, relative to the physical distribution. Higher risk aversion pushes up the price of insurance against aggregate downside risks. Because risk aversion only interacts with aggregate shocks, the price of insurance against idiosyncratic risks is unchanged. As a result, a rise in risk aversion leads to a decline in the basket-index spread, all else equal. This effect is illustrated in Figure 5, which plots basket-index spreads for various levels of correlation (panel A) and volatility (panel B).

Risk-neutral correlation among stocks offers another characterization of the effect that risk aversion has on option spreads. It directly reflects the relative price of individual stock options and options on the index. In our model, the risk-neutral stock correlation exceeds the physical correlation

$$\rho^* = \frac{\rho + \rho\omega^*(\theta^{*2} + \delta^2)}{1 + \rho\omega^*(\theta^{*2} + \delta^2) + (1 - \rho)\omega(\theta^2 + \delta^2)} \geq \rho$$

as long as jumps are on average negative and correlation is positive (as in the data), and the difference between the risk-neutral correlation ρ^* and the actual correlation ρ increases as α increases. When risk-neutral correlations are high, the value of insurance against aggregate risks dominates the value of insurance against idiosyncratic events, and the basket-index spread is narrow. We report empirical evidence on risk-neutral correlations in Section VE.

In summary, the MJ model demonstrates that a rise in risk premia tends to lower the basket-index spread. We argue that financial sector crisis spreads are puzzlingly large, and a surge in risk aversion during the crisis deepens the puzzle. If anything, a risk aversion argument for high spreads would require that investors became especially risk *tolerant* during the crisis.

III. Quantitative Assessment

In this section we build on the conceptual framework of Section II to quantitatively assess the consistency between observed crisis spreads and the predictions of

TABLE 2—CORRELATIONS AND VOLATILITIES

	Realized corr.		Implied corr.		Realized vol.		Implied vol.	
	Fin.	Nonfin.	Fin.	Nonfin.	Fin.	Nonfin.	Fin.	Nonfin.
Pre-crisis								
Mean	0.49	0.37	0.52	0.41	0.15	0.16	0.15	0.16
Max	0.78	0.51	0.81	0.53	0.35	0.31	0.28	0.27
Crisis								
Mean	0.67	0.54	0.65	0.46	0.68	0.35	0.41	0.25
Max	0.84	0.69	0.93	0.63	1.16	0.70	0.75	0.40
Crisis minus pre-crisis								
Mean	0.18	0.17	0.13	0.05	0.53	0.20	0.69	0.08

Notes: The left four columns summarize return correlations among stocks in each sector and the right four columns summarize return volatilities of sector indices. For each day in the sample, we calculate realized return correlations and index volatilities using a rolling three-month estimation window. Daily implied correlations and implied index volatilities are calculated using call options with delta of 25. Volatilities are annualized. We report averages and maxima of daily values for the financial and nonfinancial sectors in the pre-crisis sample (January 2003 to July 2007) and crisis sample (August 2007 to June 2009).

canonical option pricing models. We conclude that the unexplained basket-index put spread for financials during the crisis is puzzlingly large.

A. Correlation and Volatility During the Crisis

We first document the increase in correlation and volatility during the financial crisis, which are the key theoretical determinants of spreads. Given estimates of the index return variance $\hat{\sigma}_{x,t}^2$, stock variance $\hat{\sigma}_{i,t}^2$, and daily weights of each stock in the index $w_{i,t}$, the average realized correlation on day t is defined as¹⁷

$$(14) \quad \hat{\rho}_t = \frac{\hat{\sigma}_{x,t}^2 - \sum_{j=1}^N w_{j,t}^2 \hat{\sigma}_{j,t}^2}{\sum_{j,i \neq j} w_{j,t} w_{i,t} \hat{\sigma}_{j,t} \hat{\sigma}_{i,t}}.$$

Variances of individual stocks and the index on day t are calculated using the three trailing months of daily returns, and weights are based on the exact index composition each day.

Table 2 reports average realized correlations among financial and nonfinancial firms. In the financial sector, average correlation increased 18 percentage points during the crisis, from 0.49 to 0.67, and peaked at 0.84 during the crisis. Nonfinancial correlations rose 17 percentage points, from 0.37 to 0.54, peaking at 0.69.

Realized correlations are backward-looking and potentially noisy since they are estimated from returns. We also report forward-looking, price-based correlations implied from delta 25 call options, which are calculated according to (14) but substitute BS implied volatility in place of backward-looking realized volatility (see Driessen, Maenhout, and Vilkov 2009). Forward-looking correlations rose by 0.13 in the financial sector, from 0.52 to 0.65, and peaked at 0.93. The rise in nonfinancial implied correlation was smaller, only 0.05, and peaked at 0.63.

¹⁷This “equicorrelation” estimator for average correlation is advocated by Engle and Kelly (2012), and arises from equalizing all pairwise correlations and inverting the definition of index variance.

Table 2 also reports the realized and implied volatilities for the stock index in each sector. The annualized realized volatility of the financial index more than quadrupled from 0.15 to 0.68 and implied volatility more than doubled. Nonfinancial realized volatility rose from 0.16 to 0.35 and implied volatility rose from 0.16 to 0.25. In the analysis below, we investigate whether this observed variation in correlation and volatility can be reconciled with the rise in financial sector put spreads during the crisis.

B. Evaluating Spreads against the Black-Scholes Model

In this section we investigate whether the observed variation in correlation and volatility can be quantitatively reconciled with financial sector crisis put spreads. To evaluate this question, we first explore the BS model as a benchmark.

To map the data to our one-factor BS model, we treat the basket as composed of many ex ante identical stocks, each of whose returns obey equation (4). We build the representative basket option as a share-weighted average of individual options in the sector, as defined in equation (1). The attributes of the representative option necessary for calculating BS prices, such as its strike price and dividend yield, are also calculated as share-weighted averages of individual option attributes.¹⁸

Model-predicted basket and index put prices $P^{BS}(\sigma)$ and $P^{BS}(\sqrt{\rho}\sigma)$ are calculated every day by setting σ equal to the BS implied volatility for the basket of OTM calls and setting ρ equal to the realized return correlation in the sector. Reestimating σ each day allows the model to account for the often drastic differences in risk levels across regimes. We also calculate BS call index prices in order to compare call and put spreads. We construct our fits for both financial and nonfinancial sectors.

Table 3 reports option prices in the BS model and in the data, quoted in cents per dollar insured. Panel A shows that given the price of the call basket and given observed return correlations, BS predicts a rise in the financial sector put spread of 1.3 cents during the crisis. The actual rise is 3.2 cents per dollar. This leaves 1.9 cents, or 60 percent of the rise, unexplained by the model (panel C).

The BS model has an important additional shortcoming in that it fails to match the level of crisis option prices in either sector during the crisis. To help account for model limitations that are common to puts and calls and common to financials and nonfinancials, we also report difference-in-differences in panel C. First, the unexplained rise in the financial sector call spread is 0.3 cents, leaving an abnormal (put minus call) rise in spreads rise of 1.6 cents. For nonfinancials (reported in panel B), the analogous difference-in-differences is only 0.1 cents. The abnormal rise in financial put spreads after triple differencing (data minus spread, puts minus calls, and financials minus nonfinancials) is 1.5 cents per dollar, or nearly 50 percent of the total rise in financial sector put spreads.

¹⁸By assuming ex ante identical stocks, our approach asks the model to fit the average option price in the basket, rather than fitting the prices of each option in the basket. Because the true basket is composed of nonidentical firms, our model fits for the basket will be biased *downward* due to Jensen's inequality. Online Appendix D shows that this bias is negligible and that our results and conclusions are unchanged when we separately fit the price of each individual option in the basket.

TABLE 3—COST OF INSURANCE IN BS MODEL

	Puts			Calls			
	Basket	Index	Spread	Basket	Index	Spread	
<i>Panel A. Financials</i>							
Model							
Precrisis	3.8	1.8	2.0	3.4	1.6	1.8	
Crisis	11.5	8.2	3.3	5.5	3.5	2.1	
Crisis diff.	7.7	6.4	1.3	2.2	1.9	0.3	
Data							
Precrisis	5.2	3.8	1.4	3.4	1.8	1.6	
Crisis	15.9	11.3	4.6	5.5	3.4	2.1	
Crisis diff.	10.6	7.5	3.2	2.2	1.6	0.5	
<i>Panel B. Nonfinancials</i>							
Model							
Precrisis	5.0	1.8	3.1	4.2	1.5	2.7	
Crisis	7.8	4.6	3.2	5.4	2.9	2.5	
Crisis diff.	2.8	2.7	0.1	1.2	1.4	-0.2	
Data							
Precrisis	6.2	3.7	2.4	4.2	1.8	2.4	
Crisis	10.0	6.7	3.3	5.4	2.5	2.9	
Crisis diff.	3.9	2.9	0.9	1.2	0.7	0.5	
	Financials			Nonfinancials			F-NF
	Put	Call	P-C	Put	Call	P-C	P-C
<i>Panel C. Data spread – model spread</i>							
Crisis diff.	1.9	0.3	1.6	0.8	0.7	0.1	1.5

Notes: Summary statistics for the cost of basket and index insurance in the BS model and in the data at daily frequencies. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured in panels A to C. The pre-crisis sample is January 2003 to July 2007 and the crisis sample is August 2007 to June 2009.

C. Evaluating Spreads against the Merton-Jump Model

We next evaluate option prices from the view of the Merton jump model. In addition to Gaussian variance and correlation estimates needed to compute BS prices, the MJ model requires an estimate of the jump risk parameters (ω, θ, δ) , as well as an estimate of investor risk aversion, α . We consider two different approaches to pinning down the additional jump parameters. In the first approach, we use parameters calibrated to match the physical distribution of returns. In a second approach, we formally estimate the jump parameters directly from option prices.

Calibrating MJ Parameters to Moments of Physical Returns.—We calibrate the physical risk parameters from realized returns on the sector index and its constituent stocks by matching simulated moments of the model with corresponding data moments reported in Table 4. We target the volatility, skewness, and kurtosis of the index return, the median volatility, skewness, and kurtosis among stocks in the basket, and the average correlation among stocks in the basket. We calculate each of these moments for the financial and nonfinancial sectors in both precrisis and crisis subsamples. These target moments are reported in the Data columns of Table 4. For

TABLE 4—MJ MODEL CALIBRATION

	Precrisis				Crisis			
	Data	Model			Data	Model		
		Median	25 percent	75 percent		Median	25 percent	75 percent
<i>Panel A. Financials</i>								
Index volatility	0.15	0.15	0.14	0.17	0.69	0.71	0.66	0.82
Stock volatility	0.21	0.21	0.21	0.25	0.87	0.87	0.81	1.00
Index skewness	-0.16	-0.01	-0.17	0.08	0.11	-0.07	-1.18	0.23
Stock skewness	-0.09	-0.03	-1.80	0.14	0.03	-0.06	-0.99	0.18
Index kurtosis	5.2	3.2	3.0	62.7	5.5	5.5	3.2	14.4
Stock kurtosis	6.4	7.8	3.1	77.7	7.4	4.6	3.2	10.7
Correlation	0.49	0.49	0.46	0.51	0.67	0.67	0.65	0.69
<i>Panel B. Nonfinancials</i>								
Index volatility	0.14	0.14	0.14	0.16	0.35	0.36	0.34	0.41
Stock volatility	0.27	0.24	0.23	0.29	0.49	0.49	0.46	0.56
Index skewness	-0.10	-0.01	-0.17	0.08	-0.07	-0.07	-2.12	0.33
Stock skewness	-0.01	-0.04	-2.35	0.18	-0.02	-0.08	-1.65	0.28
Index kurtosis	4.3	3.2	3.0	66.7	6.9	11.2	3.4	44.4
Stock kurtosis	8.6	11.4	3.1	76.2	6.8	7.8	3.3	26.6
Correlation	0.37	0.37	0.34	0.40	0.54	0.54	0.52	0.56

Notes: Panel A shows data and simulated moments in the MJ model at jump parameters $(\omega, \theta, \delta) = (7, -0.05, 0.25)$, which are held fixed across all sectors and both subsamples. The volatility and correlation parameters vary across the precrisis and crisis samples and across sectors. For financials, these are set at $\sigma = 0.21$ and $\rho = 0.49$ in the precrisis sample, and $\sigma = 0.79$ and $\rho = 0.67$ during the crisis. For nonfinancials, these are 0.23 and 0.37 precrisis, and 0.45 and 0.54 during the crisis. Simulated moments and their quantiles are based on 10,000 samples of 1,635 observations.

nonfinancials we report the median moment across nonfinancial sectors stocks and indices.¹⁹

To calculate model-based moments, we choose three jump parameters (ω, θ, δ) and we hold these fixed for all sectors and all subsamples. To match differences in moments across sectors and from precrisis to crisis, we vary only σ and ρ . For financials, we fit data moments using $\sigma = 0.21$ and $\rho = 0.49$ in the precrisis sample, and $\sigma = 0.79$ and $\rho = 0.67$ during the crisis. For nonfinancials, the calibrated σ and ρ are 0.23 and 0.37 precrisis, and 0.45 and 0.54 during the crisis. Model moments are calculated from random samples with the same number of observation as the data: 1,152 daily returns are drawn using precrisis parameters, and 483 daily returns are drawn using crisis parameters. We calculate the median and interquartile range of sample moments across 10,000 simulations. The jump parameters $(\omega, \theta, \delta) = (7, -0.05, 0.25)$ minimize the distance between the model and data moments.

Table 4 reports the calibration results (Model columns). Panels A and B show moments for the financial and nonfinancial sectors, respectively. Overall, the model provides an accurate description of stock return data, as each data moment falls within the simulated interquartile range (IQR). We match the index and basket variance and correlation nearly exactly and the IQR for these moments is narrow. Our match of skewness and kurtosis is somewhat less accurate but, as the IQRs demonstrate, these moments are particularly difficult to pin down. Changes in σ and ρ

¹⁹The volatilities in Table 4 are standard deviations of daily returns in each subsample, which differ slightly from the average rolling volatilities reported in Table 2.

appear sufficient to capture observed variation in the return distribution across time and across sectors.

The last parameter necessary to compute MJ option prices is the coefficient of risk aversion, α . Instead of calibrating α , we conduct a sensitivity analysis over a wide range of values. This approach has the benefit of tracing out the effect that risk aversion has on the basket-index put spread and is discussed further below.

MJ Option Prices from Physical Calibration.—Our procedure for calculating MJ model prices follows the same approach used for BS. Each day we recover σ by setting the observed call basket price equal to the model price, and inverting the MJ formula holding all other parameters fixed at their calibrated values. In our parameterization, σ acts to shift the overall level of variance, holding fixed the proportions of return variance coming from jump shocks versus Gaussian shocks. Thus, choosing σ to match basket calls each period accommodates differences in risk levels across regimes, in direct analogy to our use of BS implied volatility in the Section IIIB. We set ρ equal to the sector's realized return correlation each day, also as in the BS analysis. We then use these estimates to price the basket of puts, the index put, and the index call using the MJ model formulae.

We first study the behavior of the MJ model setting risk aversion to zero, which gives the model its best chance to produce a large crisis put spread according to the argument in Section II. The fitted values are reported in Table 5 alongside the values from the data. While the MJ model fits the level of put and call options prices slightly better than the BS model, the MJ model with $\alpha = 0$ is still unable to produce high put prices in either sector during the crisis. More importantly, it produces a worse fit for the basket-index put spread in the financial sector. Of the 3.2 cent rise in the financial put spread during the crisis, 2 cents is left unexplained by the MJ model, versus 1.9 cents unexplained by BS. The large spread remains unique to financial sector puts during the crisis. After differencing the data versus the MJ model, puts versus calls, and financials versus nonfinancials, the unexplained rise in financial put spreads is 1.7 cents per dollar, compared to 1.5 cents versus the BS model.

Table 6 summarizes the model fit as we increase risk aversion from zero to five. Rows 1–2 and 4–5 show model-predicted put price levels for the basket and index in each subsample. Put price levels are increasing in α because risk averse investors assign higher value to insurance against downside outcomes, allowing the MJ model to generate high levels of index put prices while simultaneously fitting call option prices.

At the same time, Table 6 highlights the tension between the risk aversion needed to match the overall level of put prices, and the risk aversion that best matches the basket-index put spread. Risk aversion raises the put price level but shrinks the basket-index spread, shown in rows 3 and 6. An increase in α increases the frequency and severity of common jumps under the risk-neutral measure, but does not affect idiosyncratic jumps. This raises the price of insurance against aggregate shocks but does not affect insurance against firm-specific shocks, so the put spread compresses. In rows 7 and 8 we see that as α increases, the predicted rise in put spreads is pulled further and further from its value in the data. This remains true after differencing the financial sector put spread versus the call spread in row 9 and versus nonfinancials in row 10. The final difference-in-differences reported in row 10 summarizes the

TABLE 5—COST OF INSURANCE IN MJ MODEL, $\alpha = 0$

	Puts			Calls			
	Basket	Index	Spread	Basket	Index	Spread	
<i>Panel A. Financials</i>							
Model							
Precrisis	3.9	1.8	2.1	3.4	1.6	1.8	
Crisis	11.6	8.3	3.3	5.5	3.5	2.1	
Crisis diff.	7.7	6.5	1.2	2.2	1.8	0.3	
Data							
Precrisis	5.2	3.8	1.4	3.4	1.8	1.6	
Crisis	15.9	11.3	4.6	5.5	3.4	2.1	
Crisis diff.	10.6	7.5	3.2	2.2	1.6	0.5	
<i>Panel B. Nonfinancials</i>							
Model							
Precrisis	5.0	1.8	3.2	4.2	1.5	2.7	
Crisis	7.8	4.5	3.3	5.4	2.9	2.5	
Crisis diff.	2.8	2.7	0.1	1.2	1.4	-0.3	
Data							
Precrisis	6.2	3.7	2.4	4.2	1.8	2.4	
Crisis	10.0	6.7	3.3	5.4	2.5	2.9	
Crisis diff.	3.9	2.9	0.9	1.2	0.7	0.5	
	Financials			Nonfinancials			F-NF
	Put	Call	P-C	Put	Call	P-C	P-C
<i>Panel C. Data spread-model spread</i>							
Crisis diff.	2.0	0.2	1.8	0.8	0.8	0.0	1.7

Notes: Summary statistics for the cost of basket and index insurance in the MJ model and in the data at daily frequencies. Fits are based on calibrated MJ jump parameters in Table 4 and risk aversion $\alpha = 0$. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

TABLE 6—THE ROLE OF RISK AVERSION FOR MJ MODEL PUT PRICES

	MJ model α						Data
	0	1	2	3	4	5	
<i>Panel A. Precrisis</i>							
(1) Basket	3.9	4.0	4.2	4.4	4.8	5.3	5.2
(2) Index	1.8	2.0	2.3	2.7	3.3	4.2	3.8
(3) Spread	2.1	2.0	1.9	1.7	1.4	1.1	1.4
<i>Panel B. Crisis</i>							
(4) Basket	11.6	11.9	12.2	12.6	13.2	13.9	15.9
(5) Index	8.3	8.7	9.3	10.1	11.2	12.6	11.3
(6) Spread	3.3	3.2	2.9	2.5	1.9	1.4	4.6
<i>Panel C. Crisis diff.</i>							
(7) Spread	1.2	1.1	1.0	0.8	0.5	0.3	3.2
(8) versus data	2.0	2.0	2.2	2.4	2.7	2.9	—
(9) versus data, calls	1.8	1.8	1.9	2.1	2.2	2.2	—
(10) versus data, calls, nonfin.	1.7	1.7	1.8	1.9	2.0	2.1	—

Notes: Costs of financial sector basket and index puts in the MJ model and in the data. Fits are based on calibrated MJ jump parameters in Table 4 and risk aversion α between 0 and 5. Rows 8–10 measure the unexplained rise in crisis put spread spreads. Row 8 differences the data versus the model, row 9 further differences put spreads versus call spreads, and row 10 further differences the financial sector versus nonfinancials. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

abnormal behavior of the financial sector put spread after comparing against calls and against other sectors, and after accounting for risk levels during the crisis via the MJ model. At the level of risk aversion most consistent with actual index option price levels during the crisis ($\alpha = 4$), the unexplained financial sector put spread is 2.0 cents per dollar, 1.7 cents when $\alpha = 0$ and 1.5 cents in BS.

In summary, accounting for non-Gaussian risk and the role of risk aversion deepens the puzzle of financial crisis spreads, and further illustrates the inconsistency of financial spreads with canonical option pricing models.

Estimating MJ Parameters from Options Data.—In the preceding analysis, MJ model parameters are calibrated to physical return data, then combined with investor preference parameters in the MJ option formula to generate model-predicted prices. This approach, advocated by Broadie, Chernov, and Johannes (2007, p. 1459), ensures that option prices are consistent with the physical distribution of returns. As these authors emphasize, this consistency “is a mild but important economic restriction on the parameters.” Others, such as Andersen, Fusari, and Todorov (2015), prefer to estimate parameters without regard for the physical return dynamics so as to avoid misspecifying them. How does the fit of the MJ model change if the model parameters are not restricted to be consistent with physical return data? Relaxing the consistency requirement gives the model better hope of fitting option prices without necessarily having to resort to a bailout explanation. In this section, we investigate the unrestricted model’s ability to explain financial sector put spreads during the crisis by estimating MJ model parameters from option prices directly.

We estimate the three jump risk parameters (ω, θ, δ) by minimizing the sum of squared average pricing errors during the precrisis and crisis samples for the basket, index, and spread of put and call options. In the financial sector, for example, these pricing errors are defined as the difference between the 18 option price moments in the left half of panel B in Table 5, and their 18 model-fitted counterparts.

For any given values of (ω, θ, δ), we calculate model-based put and call prices for each day in our sample imposing three constraints. First, we continue to set model correlations equal to realized return correlations each day. To do so, on each day t , we set ρ equal to the empirical value computed via equation (14). Allowing for arbitrary correlations would allow an unrestricted model to mechanically fit any set of index and basket option prices, and our central empirical contribution is to show that spreads are too large given the observed correlations. Second, on each day t , we invert σ from the call basket price via the MJ formula, as in our earlier analyses. This allows the overall level of risk in the model to vary in a manner consistent with observed call option price dynamics. Lastly, we fix risk aversion at $\alpha = 1$. Because we estimate the model separately for each sector, fixing α imposes the basic restriction that all sectors are priced with the same risk-aversion parameter, yet avoids the computational complexity of joint estimation for all sectors.²⁰

From the daily fits, we compute the 18 model moments for put and call prices during the precrisis and crisis given the initial parameter guess and compute average pricing errors (deviations between model and data moments). We use a global

²⁰ As demonstrated above, higher risk aversion makes it even more difficult to match observed put spreads. Fixing $\alpha = 0$ produces results that are quantitatively similar to those shown here for $\alpha = 1$.

optimization algorithm to iteratively search for the values of (ω, θ, δ) that minimize the sum of squared average pricing errors.²¹

We estimate the MJ model for each of the nine sectors separately and report value-weighted averages across the nonfinancial sectors. The fits are shown in panel A of Table 7. The estimated model is able to produce substantially higher crisis put price levels in all sectors. But, most importantly, the unexplained financial sector put spread (differenced versus the model, versus calls, and versus nonfinancials) is 2.0 cents per dollar, on par with the worst fitting models in line 10 of Table 6.

The success in matching put price levels is due to the substantially higher jump risk estimates (panel D) relative to the physical calibration. The average jump size for financials is -34 percent based on options prices. The aggregate jump intensity, defined as $\omega_x = \rho\sigma^2\omega$ in the MJ specification of Section IIB, gives the expected number of jumps in a given year. For the financial sector, ω_x is 0.11 on average based on the estimates in panel D, meaning that we expect roughly 11 sector-wide price jumps every 100 years. For nonfinancials, the average jump size is -7 percent and the average ω_x is 0.29.²² We provide a detailed discussion of the point estimates for jump parameters in online Appendix H. These financial sector fits are consistent with the theoretical arguments in Section II. Comparative statics suggest increased jump risks will indeed increase put price levels. But, when coupled with sharply rising crisis correlations, this will typically *lower* the crisis put spread. The overall conclusion from this table is consistent with earlier sections: The MJ model cannot simultaneously explain the high levels of put option prices and the large basket-index put spread for financials, even when the estimated risk-neutral distribution is allowed to deviate from the observed physical distribution of returns.

IV. Can a Bailout Solve the Financial Sector Spread Puzzle?

Our findings up to now indicate that the large increase in the basket-index put spread for financials relative to nonfinancials cannot be accounted for by volatility and correlation dynamics during the crisis. In this section, we show that the observed financial put spread dynamics *can* be accounted for by option pricing models once a collective government guarantee is introduced.

²¹We use the simulated annealing algorithm `simulannealbnd.m` in Matlab's Global Optimization Toolbox which is designed for optimizing over surfaces that may contain many local optima. The σ values implied from call basket prices are recomputed at each iteration in the minimization routine based on the prevailing jump parameter values. Estimation with global optimizers is especially time intensive and, to improve estimation speed, we use a 250 day subset of our full 1,635 day sample for estimation. The 250 days are selected as follows. We split the sample into 13-day intervals and select the 2 days with the maximum and minimum basket-index put spread in each interval. This reproduces the time series dynamics and data moments from the full sample with high fidelity. The mean absolute difference between each of the 18 moments estimated from the 250-day subsample and those from the full sample is less than 0.1 cents per dollar.

²²The average value of ω_x is calculated based on daily estimates of σ inverted from OTM calls using the MJ pricing formula, daily estimates of ρ using realized correlations among stocks in the sector, and the value of ω estimated from options data. The reported ω_x is the time series average of daily estimates over the full sample. The ω_x for nonfinancials is also averaged across sectors using value weights.

TABLE 7—COST OF INSURANCE: MJ MODEL ESTIMATED FROM OPTIONS DATA

	Puts			Calls			
	Basket	Index	Spread	Basket	Index	Spread	
<i>Panel A. Financials</i>							
Model							
Precrisis	5.0	3.1	1.9	3.4	1.6	1.8	
Crisis	14.4	11.9	2.5	5.5	3.4	2.1	
Crisis diff.	9.4	8.8	0.6	2.2	1.9	0.3	
Data							
Precrisis	5.2	3.8	1.4	3.4	1.8	1.6	
Crisis	15.9	11.3	4.6	5.5	3.4	2.1	
Crisis diff.	10.6	7.5	3.2	2.2	1.6	0.5	
<i>Panel B. Nonfinancials</i>							
Model							
Precrisis	6.2	3.4	2.8	4.2	1.2	3.0	
Crisis	9.6	6.9	2.7	5.4	2.5	2.9	
Crisis diff.	3.5	3.6	-0.1	1.2	1.3	-0.1	
Data							
Precrisis	6.2	3.7	2.4	4.2	1.8	2.4	
Crisis	10.0	6.7	3.3	5.4	2.5	2.9	
Crisis diff.	3.9	2.9	0.9	1.2	0.7	0.5	
	Financials			Nonfinancials			F-NF
	Put	Call	P-C	Put	Call	P-C	P-C
<i>Panel C. Data spread: model spread</i>							
Crisis diff.	2.6	0.2	2.3	1.0	0.6	0.4	2.0
	ω	θ	δ	ω_x	ω_s		
<i>Panel D. Parameter estimates financials</i>							
	3.2	-0.34	0.54	0.11	0.07		
<i>Panel E. Parameter estimates nonfinancials</i>							
	739.2	-0.07	0.40	0.29	0.34		

Notes: Summary statistics for the cost of basket and index insurance in the MJ model and in the data (panel A for financials, panel B for nonfinancials), and their difference (panel C). Fits are based on MJ parameters estimated from options data, and panel D reports parameter estimates (ω, θ, δ) for the financial sector and the equal-weighted average of parameters for the eight nonfinancial sectors. Panel D also reports the full sample average intensity of sector-wide jumps, $\omega_x = \rho\sigma^2\omega$ and idiosyncratic jumps, $\omega_s = (1 - \rho)\sigma^2\omega$, where σ^2 is estimated from OTM calls each day and ρ is the daily realized correlation among stocks within the sector. Risk aversion is $\alpha = 1$. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

A. MJ Model with Bailouts

We embed a government bailout in the MJ model. The bailout truncates the lower tail of the financial sector index, which protects index equity holders against large losses. However, the government does not insure idiosyncratic losses of any individual bank in the index. Our bailout can also be viewed as a free put option that the government bestows upon investors in the financial sector index. This model provides a stylized illustration of how collective bailout guarantees can produce a large put spread even when correlations among stocks in the sector are rising.

The government guarantee augments the original MJ model in equation (10) to cap the log index return from below at \underline{x} . The model from Section II becomes

$$\begin{aligned} \tilde{r}_x &= \max[r_x, \underline{x}] \\ r_s &= \tilde{r}_x + \mu_s + \sqrt{1 - \rho} \epsilon_s + J_s . \end{aligned}$$

As before, we model annual returns and options with one year maturity.²³ By removing aggregate risk from the financial sector, a bailout reduces the equity risk premium component of the equilibrium price drift μ_x relative to the no-bailout case. We derive the expression for μ_x and for the mean of the stochastic discount factor (SDF) in online Appendix F. The derivation rules out arbitrage opportunities and ensures appropriate martingale dynamics for stock and index prices under the risk-neutral measure: $E^*[e^{-r_f} S_{t+1}] = S_t$.

A technical contribution of this paper is to derive closed-form expressions for the prices of European put and call options on the index and individual stock in the MJ model with a bailout.

PROPOSITION 1: *The price of a one-year put option with strike price K on a stock with price $S_0 = 1$ in the presence of a bailout \underline{x} is given by*

$$\begin{aligned} Put &= E[\exp(m)[K - \exp(r)]^+] = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} \frac{e^{-\omega_x} \omega_x^i}{i!} \frac{e^{-\omega_I} \omega_I^j}{j!} Put_{i,j} \\ Put_{i,j} &= -E[\exp(m+r) 1_{k>r}] + KE[\exp(m) 1_{k>r}] \\ &= -(V_{11} + V_{12}) + (V_{21} + V_{22}). \end{aligned}$$

$Put_{i,j}$ is the option price conditional on i aggregate jumps and j idiosyncratic jumps. Online Appendix F contains closed-form expressions for V_{11} , V_{12} , V_{21} , and V_{22} which distinguish between states of the world where the bailout is activated and not activated. The price of calls are also derived and put-call parity holds.

B. Quantitative Assessment

We estimate the MJ bailout model using financial sector options data following the identical approach used to estimate the no-bailout model in Section IIIC. The exception is that we now estimate one additional parameter—the bailout size, \underline{x} .

The estimation results are reported in Table 8. The estimated bailout in logs is 45 percent, which implies that the bailout in levels is $\exp(\underline{x}) = 0.64$. That is, investors believe that the government will not allow the financial sector index price to fall by more than 36 percent. In other words, the bailout removes a large fraction of the downside risk from the financial sector.

²³By matching the frequency of the return process and the option maturity, we avoid the possibility that the index hits the bailout floor before the contract expires. Since we are pricing European options, this approach is internally consistent.

TABLE 8—FINANCIAL SECTOR COST OF INSURANCE: MJ BAILOUT MODEL

	Puts			Calls		
	Basket	Index	Spread	Basket	Index	Spread
<i>Panel A. Model</i>						
Precrisis	5.7	5.1	0.6	3.4	0.5	2.9
Crisis	15.7	12.2	3.4	5.5	2.2	3.4
Crisis diff.	10.0	7.2	2.8	2.2	1.7	0.5
<i>Panel B. Data</i>						
Precrisis	5.2	3.8	1.4	3.4	1.8	1.6
Crisis	15.9	11.3	4.6	5.5	3.4	2.1
Crisis diff.	10.6	7.5	3.2	2.2	1.6	0.5
<i>Panel C. Data spread: model spread</i>						
Crisis diff.	Financials			F–NF		
	Put	Call	P–C	P–C		
Crisis diff.	0.4	0.1	0.3	0.0		
	ω	θ	δ	$\exp(\underline{x})$	ω_x	ω_s
<i>Panel D. Financial sector parameter estimates</i>						
	37.9	–0.75	2.47	0.64	0.008	0.005

Notes: Summary statistics for the financial sector cost of basket and index put and call prices in the MJ bailout model (panel A), in the data (panel B), and their difference (panel C). The last column in panel C compares the unexplained difference in put and call spreads for the financial sector (including a bailout) with that of the nonfinancial sector (excluding a bailout). Fits are based on MJ bailout model parameters estimated from options data, and panel D reports jump parameter estimates (ω , θ , δ) and estimated bailout threshold $\exp(\underline{x})$. Panel D also reports the full sample average intensity of sector-wide jumps, $\omega_x = \rho\sigma^2\omega$, and idiosyncratic jumps, $\omega_s = (1 - \rho)\sigma^2\omega$, where σ^2 is estimated from OTM calls each day and ρ is the daily realized correlation among stocks within the sector. Risk aversion is $\alpha = 1$. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

Option price fits from the estimated bailout model are reported in panel A of Table 8. The combination of large jump risk and a sizable bailout is successful in producing a large put spread during the financial crisis. Large jump risks maintain a high overall put price level, evidenced by a basket put price of 15.7 cents per dollar during the crisis in the model, versus 15.9 cents in the data. The bailout prevents the price of the index from rising by as much as the basket, producing a rise in the crisis put spread of 2.8 cents per dollar in the model, compared to 3.2 cents in the data, and compared to 0.6 cents for the no-bailout model shown in Table 7.

After accounting for a bailout in the model, the unexplained rise in put spreads is only 0.3 cents after differencing with calls. This difference-in-differences falls to zero after subtracting the unexplained difference in put and call spreads for nonfinancials (where the nonfinancial fits are based on the estimated no-bailout model).

Figure 6 plots the time series of financial sector basket-index put spreads in the data and in the MJ model with and without a bailout. Incorporating a bailout greatly improves the model's performance during the crisis and matches much of the run-up in financial sector put spreads.²⁴

²⁴To explore the behavior of put spreads under an alternative view of the bailout, we have also considered a case in which investors believe the index will never be allowed to fall below a fixed dollar value. Specifically, we assume that the government insures the index value at \$6, a choice based on the realized path of the financial

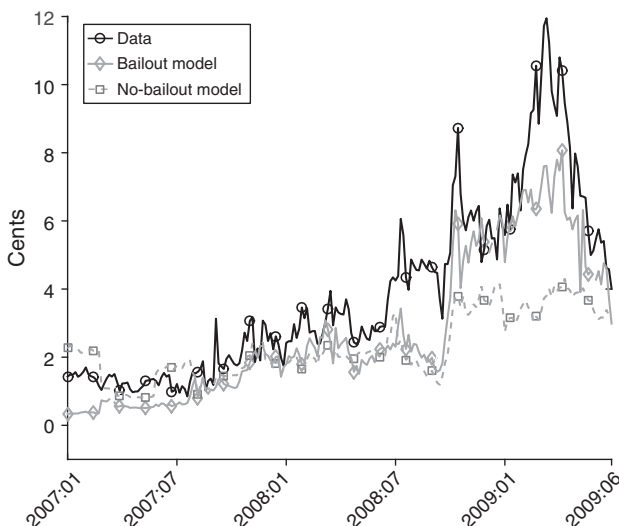


FIGURE 6. BASKET-INDEX SPREADS IN BAILOUT MODEL

Notes: Basket-index put spreads for the financial sector in the data (marked by circles) and in the MJ model with bailouts (marked by diamonds) and without bailouts (marked by squares). Fits for each model are based on the jump parameters estimated from options data and are reported in the main text. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

In order to match the high level of put prices in the presence of a bailout, the estimated model compensates with a high degree of jump risk. The jump risk parameters for the financial sector (ω, θ, δ) are estimated at $(37.9, -0.75, 2.47)$, versus values of $(3.2, -0.34, 0.54)$ in the no-bailout model. The bailout estimation requires more underlying jump risk because many of these jumps are truncated by the bailout.²⁵ The estimated bailout model behaves similarly to a rare disaster model, where the size of the aggregate disaster is given by the size of the bailout. That is, if a sector-wide jump occurs, it is essentially guaranteed to trigger the bailout. This concentrates probability mass at the estimated bailout threshold of -36 percent. But the occurrence of a sector-wide jump is also very infrequent, occurring with probability 0.8 percent each year.²⁶ This feature is unique to financials. For nonfinancial sectors, our estimates imply more frequent and smaller downward jumps. Online Appendix H explains the point estimates further and shows that the various parameters of the bailout model are well identified. Online

index, which bottomed out at \$6.18 in March 2009. Fitted put spreads from this alternative bailout are plotted in online Appendix I, and are qualitatively similar to our main bailout specification. The alternative specification more accurately matches the peak in crisis put spreads, while our main specification generates a larger average spread during the crisis.

²⁵Note that estimates of jump parameters (θ, ω, δ) in the MJ bailout model are not directly comparable to those in the no-bailout model or to past options literature. The bailout eliminates much of the risk represented by these parameters, giving them a different economic interpretation.

²⁶The probability of a sector-wide jump is determined by $\omega_X = \rho\sigma^2\omega$. For the financial sector, the value of σ inverted from call options is less than 2 percent on average over the full sample (compared to over 20 percent in the BS model), indicating that Gaussian risk is largely crowded out by the large jump parameters estimates in Table 8. The correlation among financial sector stocks is over 50 percent on average. With ω estimated at 37.9, the implied aggregate jump intensity, ω_X , is 0.008 on average over the full sample.

Appendix J assesses the robustness of our parameter estimates by reestimating the model using delta 35 options in place of delta 25 options, and shows that the option price fits, the bailout estimate, and the jump risk estimates are similar for both datasets (see Table J2).

C. *The Size of the Subsidy*

How large are the implied government subsidies to shareholders of financial sector equity? We use the bailout model as a laboratory for counterfactual analysis. Specifically, we compare the predicted cost of index insurance in the MJ model with and without a bailout guarantee, holding the level of underlying risks fixed between the two settings. In particular, we use the estimated jump risk parameters and the daily implied volatilities from the MJ bailout model to calculate option price fits in the counterfactual no-bailout model. Option prices in the counterfactual model provide an answer to the question: what would prices of traded financial sector equity insurance have been, assuming the same risk levels observed during the crisis, but in the *absence* of a government guarantee? Absent a bailout, index put options are substantially more expensive. The difference in prices between the bailout model, and the same risk parameterization under a hypothetical no-bailout scenario, provide an estimate of the insurance subsidy that the government bestowed upon financial sector equity holders.

In the absence of a bailout, we estimate that the cost of insuring against a financial sector index crash risk would have been 26.6 cents per dollar insured using delta 25 puts. The cost of the same insurance is 7.2 cents on average in the presence of a guarantee, based on the estimated no-bailout model. The implied government subsidy to financial index equity holders is 19.4 cents per dollar of insurance, which amounts to a 73 percent subsidy of the price of financial sector crash insurance.

We calculate the dollar value of the subsidy by considering the cost of insuring the total market value of US financial sector equity against a crash using delta 25 puts. First, we multiply the price of the index put in cents per dollar insured (the empirical quantity studied throughout) by the ratio of the put's strike price to the index price per share. This gives the price of insuring \$1 of financial sector equity with an OTM put. Multiplying this by the total market value of financial sector equity gives the dollar cost of insuring the entire financial sector:

$$\begin{aligned} \text{Total Dollar Cost of Insurance} &= \frac{\text{Put Price}}{\text{Strike Price}} \times \frac{\text{Strike Price}}{\text{Share Price}} \\ &\quad \times \text{Total Equity Value.} \end{aligned}$$

The collective average insurance savings due to the government guarantee in our sample amounts to \$282 billion, or 16.4 percent of the total equity value of the financial sector. These estimates are admittedly coarse and derived from a highly stylized model, thus they are not to be interpreted as estimates with high statistical precision due to uncertainty about the correct model specification. Nonetheless they suggest meaningful effects of government guarantees on the value of equity and equity-linked securities.

TABLE 9—MODEL COMPARISON BY SECTOR

	Fin.	Cons. disc.	Cons. stapl.	Energy	Health	Ind.	Mat.	Tech.	Util.
<i>Panel A. Improvement in model fit due to bailout</i>									
All moments	6.9**	2.6*	1.1	0.0	0.0	0.0	1.9	0.0	1.5
Crisis puts	5.5**	1.9*	0.7	0.0	0.0	0.0	1.2	0.0	0.0
<i>Panel B. Implied subsidies during crisis</i>									
Index CPDI	19.4	3.5	2.4	0.0	0.0	0.0	4.7	0.0	7.5
\$ billion	282.1	25.1	24.7	0.0	0.0	0.0	12.3	0.0	20.4
Percent of mkt. val.	16.4	3.0	2.1	0.0	0.0	0.0	4.0	0.0	6.5

Notes: Distance statistic comparing the average pricing errors of the bailout to the no-bailout model. The pricing errors in the first row are based on all 18 moments employed in estimation, while the second row reports the distance based only on the index put price and the basket-index put spread during the crisis. The test statistic for the distance between models is based on these crisis put moments and their covariance matrix. The sectors are financials, consumer discretionary, consumer staples, energy, health, industrials, materials, technology, and utilities.

**The bailout model fit significantly improves over the no-bailout model at the 0.1 percent level.

*The bailout model fit significantly improves over the no-bailout model at the 1 percent level.

D. Statistical Evaluation and Sectoral Comparison

The MJ models with and without a bailout are nested, which allows us conduct a GMM test of the distance between the restricted (no-bailout) and unrestricted (allowing for a bailout) versions of the MJ model. Model distance is measured as the difference in the optimized value of the objective function in our estimation—the sum of squared deviations between model and data moments—which summarizes how much better the MJ model fits when allowing for a bailout.

A bailout in the financial sector reduces the sum of squared pricing errors by 37 percent, from 18.8 in the no-bailout model to 11.9 with a bailout. Eighty percent of the reduction in squared pricing errors (5.5 of 6.9) comes from improving the model's match of two moments: the average crisis put basket price and the average crisis put spread.

The difference in fits is reported in the first column of panel A of Table 9, along with a test of significance for the difference in model fits. The test statistic is the generalized method of moments (GMM) distance metric, defined as²⁷

$$\text{Distance} = \mathbf{M}'_{\mathbf{U}} \mathbf{V}(\mathbf{M}_{\mathbf{U}})^{-1} \mathbf{M}_{\mathbf{U}} - \mathbf{M}'_{\mathbf{R}} \mathbf{V}(\mathbf{M}_{\mathbf{U}})^{-1} \mathbf{M}_{\mathbf{R}}.$$

$\mathbf{M}_{\mathbf{U}}$ and $\mathbf{M}_{\mathbf{R}}$ are the average pricing error vectors estimated in the unrestricted (bailout) and restricted (no-bailout) models, respectively. $\mathbf{V}(\mathbf{M}_{\mathbf{U}})$ is the pricing error covariance matrix under the unrestricted model. As our results throughout indicate, the central challenge facing the model is its ability to capture the behavior of puts prices during the crisis. Therefore, our tests define $\mathbf{M}_{\mathbf{U}}$ and $\mathbf{M}_{\mathbf{R}}$ as the pricing errors for the crisis put basket and put spread. $\mathbf{V}(\mathbf{M}_{\mathbf{U}})$ is estimated from the time series of pricing errors in the unrestricted model using Newey-West with 20 lags. Because two moments are used, the test statistic, $T \cdot \text{Distance}$, is asymptotically distributed

²⁷See, e.g., Hayashi (2000).

as $\chi^2(2)$, where T is the number of time series observations used in the average pricing error calculation.²⁸

According to this test, the model improvement from incorporating a bailout in the financial sector is highly significant (p -value < 0.001). Panel A of Table 9 reports the same model comparison for the eight nonfinancial sectors. For four sectors (energy, healthcare, industrials, and technology), the bailout (defined as $\exp(\underline{x})$) is estimated to be zero in the unrestricted specification, thus there is zero distance between the restricted and unrestricted models. In the remaining four sectors, the unrestricted model estimates a positive bailout. In three of these four sectors (consumer staples, materials, and utilities), the quantitative improvement due to the bailout is small (less than 30 percent of the improvement seen in the financial sector) and is statistically insignificant. Only one other sector, consumer discretionary, statistically rejects the no-bailout model in favor of a bailout. Notably, consumer discretionary includes the automotive manufacturers that benefited from an explicit government bailout during the crisis. But even in this sector the improvement in fits of 2.6 is relatively small, less than 40 percent of the improvement in the financial sector.

To evaluate the economic significance of the estimated bailout model in nonfinancial sectors, we repeat the same subsidy calculations presented earlier for financials. The results are reported in panel B of Table 9. The economic magnitudes of nonfinancial sector subsidies are small. Compared to the 19.4 cents per dollar subsidy for financials, the next biggest subsidy is 7.5 cents for utilities. But, as shown in panel A, this number is statistically insignificant as we cannot reject the no-bailout model for utilities. In aggregate dollar terms, the next biggest subsidy is \$25.1 billion in the consumer discretionary sector, less than one-tenth of the total subsidy calculated for financials.

V. Additional Evidence

A. Direct Evidence from Government Announcements

Our stylized model assumes that investors know the level of the bailout with certainty.²⁹ In reality, investors are uncertain about the nature of a bailout and are likely to update their bailout beliefs as events unfold. In this section, we provide evidence that the dynamics of the basket-index spread are closely tied to government policy announcements during the financial crisis of 2007–2009. Under the collective bailout hypothesis, an increase in the probability of a financial disaster increases the basket-index put spread. We focus on significant announcements for which we can determine the *ex ante* sign of the effect on the likelihood (and size) of a collective bailout. Our evidence suggests that put spreads respond to government announcements in a manner consistent with the collective bailout hypothesis.

We identify seven events that increase the probability of a government bailout for shareholders of the financial sector: (i) July 13, 2008: Paulson requests government

²⁸Of the 250 observations used in estimation, 74 of these correspond to the crisis, hence this is the value of T used in the test statistic.

²⁹Online Appendix G extends the MJ option pricing model to the case of an uncertain bailout. A numerical example illustrates that put prices in this model are slightly higher than the probability-weighted average of the put prices in the certain bailout and no-bailout models.

funds for Fannie Mae and Freddie Mac; (ii) October 3, 2008: Revised bailout plan Troubled Asset Relief Program (TARP) passes the US House of Representatives; (iii) October 6, 2008: The Term Auction Facility is increased to \$900 billion; (iv) November 25, 2008: The Term Asset-Backed Securities Loan Facility (TALF) is announced; (v) January 16, 2009: Treasury, Federal Reserve, and the FDIC provide assistance to Bank of America; (vi) February 10, 2009: The Federal Reserve announces it is prepared to increase TALF to \$1 trillion; (vii) March 3, 2009: Treasury and Federal Reserve launch TALF. We refer to these as positive announcement dates.

We also identify seven negative announcements that we expect decreased the probability of a bailout from the *ex ante* view of shareholders: (i) March 16, 2008: Bear Stearns is bought for \$2 per share; (ii) September 7, 2008: Treasury announces plans to place Fannie Mae and Freddie Mac into conservatorship; (iii) September 15, 2008: Lehman Brothers files for bankruptcy; (iv) September 29, 2008: House votes no on the bailout plan; (v) October 14, 2008: Treasury announces \$250 billion capital injections; (vi) November 7, 2008: President Bush warns against too much government intervention in the financial sector; and (vii) November 13, 2008: Paulson indicates that TARP will not be used to buy troubled assets from banks.

We study the unexplained put spread (data minus MJ model, financials minus nonfinancials) around announcement dates. Financial sector basket-index put spreads rise 0.75 cents per dollar in the five days following a positive announcement, relative to nonfinancials. This represents a 31 percent increase relative to the average spread for financials. Spreads fall on average by 0.89 cents per dollar in the five days following a negative announcement, or by 38 percent of the average financial sector spread. Panel A of Figure 7 plots these positive announcements results in event time for financials. Panel B plots the negative announcement effects.

The largest positive effect occurred after the government announced the launch of TALF, which was designed to stimulate securitization markets by providing financing to institutions with large exposures to asset-backed securities. The announcement included the date when the first funds would be disbursed and stated that interest rates and haircuts would be lower than previously planned. In the five days following the announcement, basket-index put spreads in the financial sector widened 2.9 cents per dollar relative to the predicted model spread and relative to nonfinancials, nearly doubling the average financial sector crisis spread.

The failures of Bear Stearns and Lehman Brothers initially reduce the basket-index put spread. The Lehman failure was then followed by an increase in the spread as the resulting turmoil convinced markets that future bailouts would be more likely.³⁰ The largest negative effect was registered on October 14, 2008 when the US Treasury announced the TARP would be used as a facility to purchase up to \$250 billion in preferred stock of US financial institutions. The Treasury essentially shifted TARP's focus from purchasing toxic assets to recapitalizing banks, thereby diluting existing shareholders. This was the start of a longer decline in the spread that was reinforced by speeches delivered by President Bush and Secretary of the Treasury Henry

³⁰For example, the rescue of AIG was announced the day after Lehman's collapse.

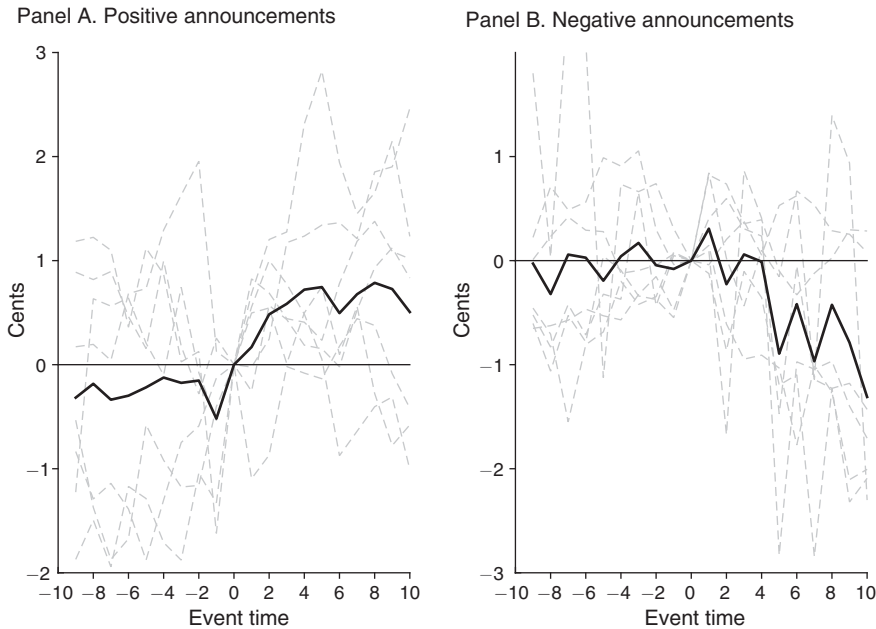


FIGURE 7. PUT SPREADS AROUND GOVERNMENT ANNOUNCEMENTS

Notes: Strike-matched basket-index put spread difference-in-differences (data minus model, financials minus non-financials) around announcement dates. Panel A shows responses to positive announcements and panel B shows responses to negative announcements. The solid line shows the average spread response over all announcements, and the dotted lines show the responses to each individual announcement. Event time is in days. Delta is 25 and time to maturity is 365 days.

Paulson in early November. Clearly, there was fear that bank shareholders would not receive the government bailout they had hoped for, and the spread dropped by 2.8 cents. This decline in the spread was reversed only in early January 2009 when the FDIC, the Federal Reserve, and the Treasury provided assistance to Bank of America and explicitly announced programs to purchase toxic assets. The put spread began its largest increase in the beginning of February 2009 and peaked in March 2009 with TALF. This appears to be the point when the crisis came under control and markets became gradually reassured that the government was committed to bailing out the financial sector without wiping out equity holders.

B. Counterfactual: The Technology Sector Crash

The value of the financial sector ETF peaked in June 2007 and fell by 83.4 percent over the subsequent 20 months. In March 2000, the technology sector crashed in a similarly dramatic fashion, with the tech/telecom ETF declining 82.3 percent from peak to trough. Unlike the financial crisis, we have no reason to believe that prices in the technology sector benefited from an implicit government bailout guarantee, making this episode a suitable “placebo” event. If standard option pricing models are unable to explain technology sector basket-index spreads in the early 2000s, this calls into question our hypothesis that bailout guarantees are responsible for large financial sector spreads in the 2007 to 2009 crisis.

TABLE 10—PUT SPREADS IN THE TECHNOLOGY SECTOR CRASH

	Puts			Calls			P-C
	Basket	Index	Spread	Basket	Index	Spread	Spread
Data	14.3	8.8	5.6	6.9	3.2	3.7	1.8
BS Model	12.9	6.8	6.1	6.9	3.0	3.9	2.2
Difference	1.4	2.0	-0.6	0.0	0.2	-0.2	-0.4

Notes: Summary statistics for the cost of basket and index insurance in the BS model and in the data for the technology sector. Sample is March 2000 to January 2002. Delta is 25 and time to maturity is 365 days. Units are cents per dollar insured.

To mirror the our financial crisis sample, we study the tech decline from March 2000 to January 2002. For this period, we compare technology sector spreads to those predicted by the BS model given observed risk dynamics.³¹ The basket-index put spread in the technology sector averaged \$0.056 during the tech crash, larger than the financial sector spread during the crisis. However, the BS model predicts a spread of 6.1 cents based on call option implied volatility and realized tech sector correlations, accounting for more than 100 percent of the tech spread. The difference-in-differences (data minus model, put minus call spread) is also negative at -0.4 cents. Hence, unlike the financial sector spread during the crisis, we find no abnormal widening of the basket-index put spread for the technology sector in the early 2000s. This fact supports our bailout interpretation of financial sector put spread behavior during the recent crisis.

C. Individual Firm Evidence

If there is heterogeneity across banks in their likelihood of being bailed out when a crisis occurs, we expect to see different prices of crash insurance across banks. Below we demonstrate that puts on the largest financial institutions appear underpriced relative to puts on smaller banks after controlling for risk, consistent with an implicit “too-big-to-fail” guarantee. We also provide evidence from credit markets that is consistent with this interpretation.

Option Market Evidence.—On each day in our sample, we run a cross-sectional regression of OTM put prices (as a fraction of underlying stock price) for each firm on the firm’s size:

$$\text{Put/Spot}_{i,t} - \text{Model fit}_{i,t} = a_t + b_t \text{Size}_{i,t-21} + c_t \text{Leverage}_{i,t-21} + e_{i,t}$$

We run separate regressions for the set of financial firms and the set of nonfinancials. To adjust for differences in risk across firms, we define $\text{Put/Spot}_{i,t}$ as the difference between observed put/spot, and the BS predicted value of put/spot based on each firm’s implied volatility extracted from OTM call options.³² Since differences in

³¹ State Street introduced Standard & Poor’s depository receipt (SPDR) sector ETFs in 1999. The technology sector is one of two sectors whose option data start in 1999.

³² Because this analysis focuses on individual stock options, we use the BS model to adjust for risk since this avoids the need for MJ model jump parameters of individual firms. If we impose that individual stock jump parameters are the same for all firms, we find the same results as in Figure 8.

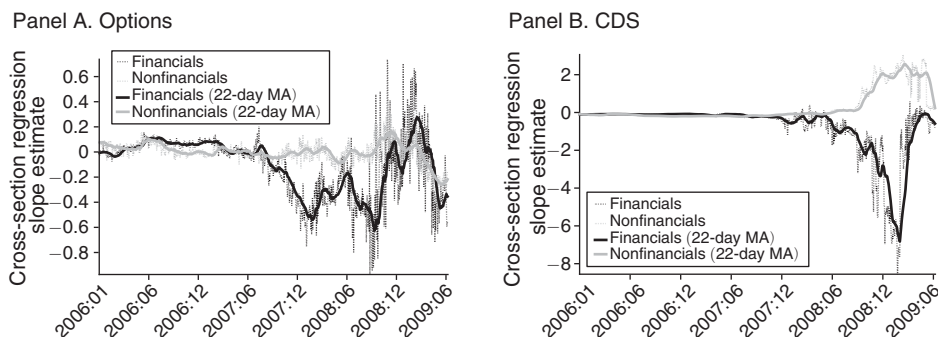


FIGURE 8. PRICE OF CRASH INSURANCE AND FIRM SIZE FROM OPTIONS AND CDS

Notes: Panel A plots size slope coefficient estimates (b_t) from cross-section regression equation $\text{Put}/\text{Spot}_{i,t} - \text{Model fit}_{i,t} = a_t + b_t \text{Size}_{i,t-21} + c_t \text{Leverage}_{i,t-21} + e_{i,t}$, where the model fit comes from BS. Size is the log of market value of equity plus book value of debt, and leverage is the log ratio of book value of assets to market value of equity. Panel B reports slope estimates from the same cross-section regression replacing the left-hand side with CDS spread $_{i,t} - \text{Model fit}_{i,t}$, where the model fit is from the Merton (1974) credit model. Regressions are run each day using stocks in the S&P 500 financial sector (black) and nonfinancial sectors (gray). Dotted lines show daily estimates and solid lines show 22-day moving averages.

leverage mechanically alter the riskiness of equity, and to be consistent with our credit tests below, we control for leverage in regression (15). We measure size as the log of market value of equity plus book value of debt. We define leverage as the log ratio of book value of assets to market value of equity. We lag both size and leverage by one month (21 trading days). If an implicit bailout guarantee benefits large banks more than small banks, we expect a negative slope coefficient (b_t) on size.

Panel A of Figure 8 plots the daily time series of the cross-sectional regression slopes b_t . The solid black line shows a 22-day moving average of the cross-section slope coefficient using the cross section of stocks in the S&P 500 financial sector index. During the crisis period, the average slope estimate on size is -0.23 . To interpret this estimate, consider that the largest 10 percent of all S&P 500 banking sector constituents are on average 9.6 times larger than the remaining 90 percent of banks in the sector (in levels). This implies that, during the crisis, puts on the largest 10 percent of banks were cheaper than the remaining 90 percent of banks by 0.52 cents per dollar insured ($0.23 \times \log(9.6)$), after adjusting for differences in bank leverage and volatility via BS. Prior to the crisis, the average difference among large and small banks was effectively zero, as the average precrisis size slope is 0.01. The figure also shows that the size discount is unique to the financial sector: The nonfinancial sector estimate of b_t is on average -0.02 during the crisis (solid gray line).

Credit Market Evidence.—Options prices for the index and the basket are ideally suited for identifying a *systemic* bailout guarantee, our main object of interest. While there is no analogous basket/index comparison that can be made with corporate credit contracts,³³ individual bank credit default swap (CDS) spreads are useful to

³³The natural object to study would be CDS on individual banks versus CDS on the financial sector index. There is a widely traded credit default index (CDX) contract which is a basket of CDS contracts. Unfortunately,

determine if bank-level crash insurance prices are influenced by sector-wide government guarantees. In particular, we show that bank size is a key driver of differences in individual bank CDS spreads even after accounting for default probabilities.

We collect daily 5-year CDS rates from Markit.³⁴ To adjust for differences in risk across financial firms, we calculate a model-implied CDS rate from the Merton (1974) model, which takes as inputs the current stock price, the book value of debt, and the stock's volatility (we use implied volatility from at-the-money (ATM) call options). As in the previous section, we run cross-sectional regression equation (15) each day, but now use as the dependent variable the observed CDS spread in excess of the model-predicted CDS rate (right-hand side variables are unchanged). The solid black line in panel B of Figure 8 shows that risk-adjusted CDS rates are lower for larger firms in the financial sector, and that this relationship steepens strongly during the financial crisis. There is no evidence of a CDS discount for large nonfinancial firms during the crisis (gray solid line). Thus, the price of crash insurance, measured from debt markets and taking into account the effects of leverage and volatility, is lower for large banks than for small banks, consistent with our evidence from the options markets.³⁵

D. Moneyness: Bending the Implied Volatility Skew

The volatility skew refers to the graph of BS implied volatilities as a function of the delta of the option, and is frequently used to summarize the pricing of options by moneyness. We analyze the slope of the volatility skew for basket and index options before and during the crisis.

Typically, the volatility skew is downward-sloping for both index and basket puts, meaning that OTM options are expensive relative to ATM options. In normal times, the slope of the volatility skew is slightly steeper (more negative) for the index than for the basket. Figure 9 plots the difference in volatility skews between the basket and the index (and differencing put versus call implied volatility). We indeed see an upward-sloping basket-index difference prior to the crisis for both the financial sector (squares) and nonfinancials (stars). In other words, OTM index put options are expensive relative to the put basket, and relative to call options. This is true in both financial and nonfinancial sectors.

During the crisis, the basket-index slope for nonfinancials (circles) remains essentially unchanged. For financials, however, the index volatility slope during the crisis drops relative to the basket, inverting the difference in volatility curves (diamonds). The basket-minus-index implied volatility reaches a maximum of 3.5 percent at delta 25 and gradually decreases to 2.5 percent at delta 55. That is, the bailout

there is no CDX index for the US financial sector. But the problem goes beyond data availability. Conceptually, the CDX is not a CDS on a portfolio in the same way an index option is. Instead, it is simply the weighted average of the individual CDS contracts of the firms in the index. CDX index tranches, which allow investors to take bets on a slice of the default distribution, could be more useful for a systemic risk comparison. But due to the absence of a finance sector-specific CDX tranches, the data are not available to infer a systemic bailout guarantee from credit derivatives.

³⁴We are able to collect CDS data for 81 financial firms and 411 nonfinancial firms that were part of the S&P 500 index over our sample.

³⁵We find qualitatively identical results in a range of alternative specifications, for example using raw put prices and CDS spreads in place of model residuals, using different measures of size such as equity value, or controlling for additional bank characteristics.

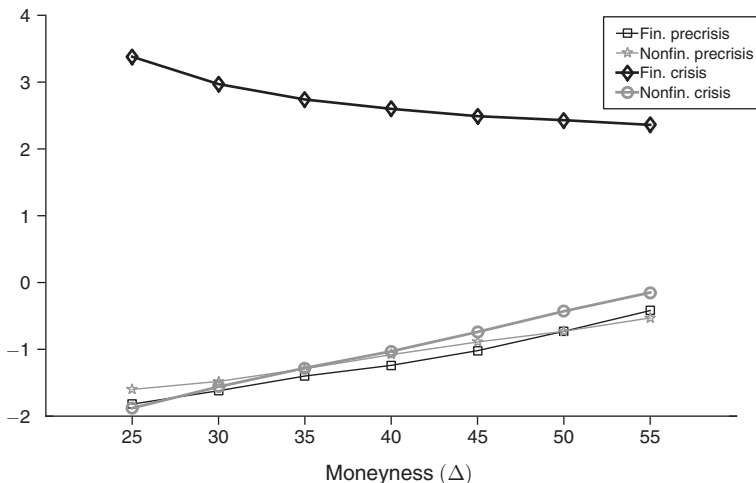


FIGURE 9. IMPLIED VOLATILITY SKEW DIFFERENCE-IN-DIFFERENCES

Notes: Average differences in BS implied volatility (basket minus index, puts minus calls) across moneyness. The vertical scale shows annualized percentages. The precrisis sample is January 2003 to July 2007 and the crisis sample is August 2007 to June 2009. Time to maturity is 365 days.

guarantee flattens the implied volatility skew for index put options. Intuitively, a government guarantee has a larger impact on index options that are deeper OTM (lower delta), since the payoff of these contracts is increasingly isolated to states of the world in which a bailout is likely to be active. While the basket also benefits to some extent from the guarantee, the effect is less than one-for-one with the index because the guarantee does not insure idiosyncratic banks shocks. This reverses the typical pattern of the differences in basket and index skews.³⁶

E. Implied Correlation

Implied correlation is a well-known metric used to compare the cost of index options versus individual stock options (Driessen, Maenhout, and Vilkov 2009). While it does not measure the value of crash insurance directly, implied correlation may be used to summarize the differential pricing of tail risk at the sector and firm levels. Much like the realized physical correlation in equation (14), $\tilde{\rho}_t$ estimates the average correlation within a sector under the risk-neutral measure. It is based on BS implied volatilities of index options ($\tilde{\sigma}_{x,t}$) and individual stock options ($\tilde{\sigma}_{j,t}$),

$$\tilde{\rho}_t = \frac{\tilde{\sigma}_{x,t}^2 - \sum_{j=1}^N w_{j,t}^2 \tilde{\sigma}_{j,t}^2}{\sum_{j,i \neq j} w_{j,t} w_{i,t} \tilde{\sigma}_{j,t} \tilde{\sigma}_{i,t}}$$

As the index option becomes cheap relative to individual options (i.e., as the basket-index spread increases), the implied correlation falls. This is a useful

³⁶We provide additional descriptive statistics for the behavior of crisis option spreads across moneyness and maturity in online Appendix J.

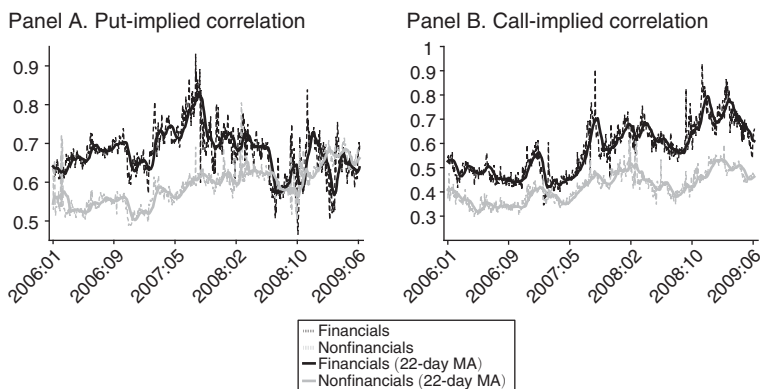


FIGURE 10. IMPLIED CORRELATIONS

Notes: Implied correlations for the financial and nonfinancial sectors from delta 25 puts (panel A) and calls (panel B). Delta is 25 and time to maturity is 365 days.

complement to the basket-index spread for two reasons. First, this metric is a correlation so the numbers are easy to interpret as the fraction of risk-neutral variance that is attributable to aggregate risk. Second, it uses BS implied volatilities as inputs to remove mechanical effects that might be due to differences in underlying prices or other contract-specific features.

We compute implied correlations for each sector and plot the time series in Figure 10. We separate results based on OTM puts and calls. For financial sector puts, the average implied correlation for financials decreases from 0.71 in the precrisis sample to 0.67 in the crisis sample, while call implied correlations rise 13 percentage points from 0.52 to 0.65. The difference-in-differences (puts minus calls) amounts to a decrease of 17 percentage points for put implied correlations among financial firms. This drop in implied correlations is unique to the financial sector. For nonfinancials, both put and call implied correlations rise, and the difference-in-differences is 0.4 percentage points. Put and call implied correlations in nonfinancial sectors also behave similarly to realized correlations reported in Table 2. The same is true for call implied and realized correlations in the financial sector. However, for financial sector puts, there is a sharp divergence between implied and realized correlations. These comparisons reinforce the put spread evidence that financial sector puts became unusually cheap during the crisis.³⁷

VI. Alternative Explanations

In Section IIC we explore a leading alternative explanation for the crisis behavior of financial sector put spreads—that the price of risk increased—and show that this explanation is inconsistent with our findings. Here we consider additional alternatives

³⁷Dynamics in put implied correlations are a mirror image of the basket-index put spread. The put implied correlation for financials peaks near 0.9 in the summer and early fall of 2007 and then begins a gradual decline. The largest decline (from 0.7 to 0.5) is in the summer of 2008 around the failure of Lehman Brothers. In late 2008, the implied correlation briefly increases again, only to fall again in March 2009.

to the collective bailout explanation for the behavior of crisis put spreads, including counterparty risk, mispricing, short sale restrictions, hedging costs, and liquidity. We conclude that none are consistent with the patterns in the data.

A. Counterparty Credit Risk

A leading alternative explanation is counterparty risk. OTM financial index put options pay off when the financial system is potentially in a meltdown. If option contracts are not honored in these states of the world, it could generate a basket-index spread increase for put options on financial firms, more so than for other firms.

All of the options traded on the CBOE are cleared by the Options Clearing Corporation (OCC), which also is the ultimate guarantor of these contracts. The writer of an option is subject to margin requirements that exceed the current market value of the contract. Positions are marked-to-market on a daily basis, with mechanically increasing margin requirements in volatile markets, and margins are exempt from bankruptcy clawbacks. In addition, the OCC has a clearing fund, and the fund size is directly tied to the volume of transactions. This clearing fund was only tapped once after the stock market crash of 1987, and the amount was small. The clearing fund was not used during the recent financial crisis, even though the volume of transactions set a new record. S&P has consistently given the OCC a AAA rating since 1993. So, counterparty risk seems limited.

Moreover, if counterparty credit risk were the driver of the basket-index spread, then the percentage effects should be much larger for shorted-dated options. Given that these contracts are marked-to-market every day, the effect of counterparty credit risk on a one-year option is of order $\sigma/\sqrt{250}$ rather than σ , because the contract is recollateralized each day as needed. However, we find that the basket-index spreads roughly increase with the square root of the maturity of the contract.³⁸

Finally, the dynamics of the basket-index spread around government announcements are inconsistent with a counterparty credit risk explanation. Announcements that increase the likelihood of a bailout increased the basket-index spread, while negative announcements decreased the spread. The counterparty credit risk explanation would predict the opposite effect.

B. Mispricing, Cost of Hedging, and Short-Sale Restrictions

Recent research has documented violations of the law of one price in several segments of financial markets during the crisis.³⁹ A few factors make the mispricing explanation a less plausible candidate for our basket-index put spread findings. First, trading on the difference between the cost of index options and the cost of the basket requires substantially less capital than some other trades (CDS basis trade, Treasury Inflation Protected Securities (TIPS)/Treasury trade) due to the implicit

³⁸The one-year crisis put spread is 4.6, while the annualized one-month spread is $1.4\sqrt{12} \approx 4.8$ for delta 25 puts (see Table J1).

³⁹In currency markets, violations of covered interest rate parity have been documented (Gârleanu and Pedersen 2011). In government bond markets, there was mispricing between TIPS, nominal Treasuries, and inflation swaps (Fleckenstein, Longstaff, and Lustig 2010). Finally, in corporate bond markets, large arbitrage opportunities opened up between CDS spreads and the CDX and between corporate bond yields and CDS (Mitchell and Pulvino 2009).

leverage in options. Hence, instances of mispricing in the basket-index spread due to capital shortages are less likely to persist (Mitchell, Pedersen, and Pulvino 2007; Duffie 2010). Second, if we attribute our basket-index spread findings to mispricing, we need to explain the divergence between put and call spreads. This asymmetry rules out most alternative explanations except perhaps counterparty risk (addressed above) and the cost of hedging.

Single-name options and index options have different costs of hedging. Single-name options are hedged with cash market transactions while index options are hedged using futures since the latter are more liquid. Hedging using cash transactions is more expensive than using futures. This affects put options more than call options since shorting a stock accrues additional costs, and these costs can be larger in times of crisis. In fact, there were explicit short sale restrictions on financial sector stocks. A short-sale ban could push investors to express their bearish view by buying put options instead of shorting stocks. Market makers or other investors may find writing put options more costly when such positions cannot be hedged by shorting stock. The SEC imposed a short sale ban from September 19, 2008 to October 8, 2008, which affected 800 financial stocks. From July 21, 2008 onward, there was a ban on *naked* short-selling for Freddie Mac, Fannie Mae, and 17 large banks.

However, exchange and over-the-counter option market makers were exempted from short-sales restrictions so that they could continue to provide liquidity and hedge their positions during the ban. Both the short window of the short sales ban compared to the period over which the put spread increased and the exemption for market makers make the short sale ban an unlikely explanation for our findings. Second, the changes in the cost of shorting do not line up with the basket-index spread dynamics. To measure short sales costs, we use securities lending fee data from the SEC for each stock in the S&P 500, and calculate value-weighted average lending fees by sector. We find little association between the put spreads and short sale costs. In the financial sector, changes in lending fees have a 3.7 percent correlation with changes in spreads, versus a correlation of -4.1 percent for nonfinancials. The correlation is insignificant in both cases with p -values over 0.25. Similarly, we find no association between put spreads and short sale quantities, both for shares on loan and for shares available to lend.

C. Liquidity

Another potential alternative explanation of our findings is that index put options are more liquid than individual options, and that their relative liquidity rose during the financial crisis. The same explanation must also apply to call options. Illiquidity is an unlikely explanation for our findings, often pointing in the opposite direction. Online Appendix K contains details, while here we summarize the main findings. These findings corroborate our bid-ask spread analysis in online Appendix C.

While one-year OTM put options have substantial bid-ask spread and limited volume, financial sector index options are more liquid than other sector index options. The liquidity difference between index and individual put options is smaller for the financial sector than for the average sector. Furthermore, during the financial crisis, the liquidity of the options increases, and it increases more for index puts than for individual puts and more in the financial sector than elsewhere. The absolute increase

in liquidity of financial sector index puts during the financial crisis and its relative increase versus individual put options suggest that financial sector index options should have become more expensive, not cheaper during the crisis. Short-dated put options are more liquid than long-dated options, and we verified above that our results are robust across option maturities. Finally, we also find that calls and puts are similarly liquid, yet they display very different basket-index spread behavior. All these facts suggest that illiquidity is an unlikely explanation for our findings.

VII. Conclusion

We uncover new evidence from option prices that suggests the government absorbed aggregate tail risk during the 2007–2009 financial crisis by providing a sector-wide bailout guarantee to the financial sector. Indirect evidence comes from the failure of standard asset pricing models to simultaneously explain (i) the relative price dynamics of financial sector index put options and puts on the basket of individual banks, and (ii) return correlations among banks. A modified version of the standard model that truncates downside risk in the financial sector does a much better job explaining put spread behavior. Direct evidence comes from studying the basket-index put spread around government announcements.

Our evidence implies that the financial sector equity holders enjoyed a sizable government subsidy in the form of free insurance against a collapse in bank stock prices. Government financial crisis policy typically aims to protect debt holders at the expense of equity holders. Instead, our analysis demonstrates how equity investors can benefit from guarantees alongside debt holders. We estimate that the insurance provided to financial sector equity investors was worth on average \$282 billion during the financial crisis.

This finding has implications for the measurement of systemic risk, which often relies on equity and equity option prices. Our results show that these prices are contaminated by the government guarantee, and that this contamination can be dramatic. Future work could extend our analysis to jointly model the dynamics of bank option, stock, and bond prices to estimate the total value of government guarantees and to estimate systemic risk after accounting for equity and option price distortions due to the guarantee. Applying our model to the European crisis is also a promising endeavor.

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