Too-Systemic-To-Fail: What Option Markets Imply About Sector-wide Government Guarantees*

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Abstract

Investors in option markets price in a substantial collective government bailout guarantee in the financial sector, which puts a floor on the equity value of the financial sector as a whole, but not on the value of the individual firms. The guarantee makes put options on the financial sector index cheap relative to put options on its member banks. The basket-index put spread rises fourfold from 0.8 cents per dollar insured before the financial crisis to 3.8 cents during the crisis for deep out-of-the-money options. The spread peaks at 12.5 cents per dollar, or 70% of the value of the index put. The rise in the put spread cannot be attributed to an increase in idiosyncratic risk because the correlation of stock returns increased during the crisis. The government's collective guarantee partially absorbs financial sector-wide tail risk, which lowers index put prices but not individual put prices, and hence can explain the basket-index spread. A structural model with financial disasters quantitatively matches these facts and attributes as much as half of the value of the financial sector to the bailout guarantee during the crisis. The model solves the problem of how to measure systemic risk in a world where the government distorts market prices.

Keywords: systemic risk, government bailout, too-big-to-fail, option pricing models, disaster models, financial crisis

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1 Introduction

Economic downturns that follow in the wake of financial crises are deep and persistent.[1] Governments seek to mitigate the risk and repercussions of financial disasters by providing implicit and explicit guarantees to financial institutions that are deemed integral to the stability of the financial system. The size and the effect of these too-systemic-to-fail government guarantees remain highly uncertain and intensely researched. We argue that equity options markets are uniquely suited to gauge the market's perception of too-systemic-to-fail guarantees. Since guarantees only kick in during a financial crisis, their effect should be most visible in the prices of assets that mostly reflect tail risk, like put options. We find that investors price in substantial government bailout guarantees for the financial sector as a whole.[2]

During the financial crisis, put options on the financial sector index reflected markedly less aggregate tail risk than did individual put option prices on the financial firms that make up the index. This notable absence of priced aggregate tail risk at the sector level is consistent with investors' perception of a strong collective bailout guarantee for the financial sector. By putting a floor under the value of the financial sector, the government eliminates part of the sector-wide tail risk, but it does not eliminate idiosyncratic tail risk. Consistent with this absorption of sector-wide tail risk, the government's guarantee of the sector flattened the well-documented volatility skew for deep-out-of-money put options on the financial sector index. We do not find similar effects on the volatility skew in other sectors of the economy. This explains why out-of-the-money (OTM) index put options were cheap during the crisis relative to the basket of individual put options.

We use the difference between the cost of a basket of options and an index option to estimate the size of the guarantee extended to the financial sector during the crisis. Figure 1 plots the dollar difference in the cost of insuring the downside risk of all firms in the financial sector and the cost of only insuring against the sector-wide downside risk. It also displays the market capitalization of the financial sector itself. The cost differential peaks at $139 billion on October 13, 2008, or

[1]See, for example, Reinhart and Rogoff (2009).

[2]In principle, bailouts of bondholders and other creditors do not imply that the value of equity is protected. However, in practice, given the uncertainty about the resolution regime, especially for large financial institutions, the collective guarantees tend to benefit shareholders as well.

10.5% of the financial index's market value. Using a structural model, we find that the collective bailout guarantee accounts for as much as half of the market value of the financial sector over our 2003-2009 sample.

Absent government guarantees, the high basket-index spread in the financial sector is puzzling. Standard option pricing logic suggests that the dramatic increase in the correlation of stock returns during the crisis should raise the price of OTM index options relative to the price of a basket of individual options with the same moneyness. This is exactly what we find for call options in all sectors of the economy. In contrast, the cost of the basket of individual stock puts soars relative to the cost of the index puts for the financial sector. This increase in the basket-index put spread is much larger for the financial sector than for any other sector. The basket-index spread for OTM put options on the financial sector index reaches a maximum of 12 cents per dollar insured in March 2009, or 70% of the cost of the index put. To generate this increase in the basket-index spread for OTM put options, the standard option model would have to assume a large increase in idiosyncratic risk relative to aggregate risk. But this would counter-factually imply a sharp decrease in stock return correlations.

A collective government guarantee for the financial sector can explain the puzzle. Intuitively, the government's collective bailout guarantee truncates the distribution of the total equity value of the financial sector, but not that of the individual stocks in the sector. Consider two OTM put options, one on the sector index and one on a representative individual stock. Assume that they share the same strike price which is below the index truncation point. An increase in the volatility of aggregate shocks will increase the correlation among stock returns and it will increase the put prices of individual stocks. However, it has no effect on the index put price. We generalize this intuition to our structural model and show that only a calibration with a bailout guarantee can simultaneously generate a high put spread and an increase in correlation between stocks.

Furthermore, a careful study of the evolution of the put spread for the financial index lends direct support to our government guarantee hypothesis. The spread increases by on average 1.61 cents (27%) in the first five days after government announcements that increase the probability of a bailout, while it decreases on average 0.85 cents (13%) after announcements that have the opposite effect. The largest increase in the spread (60%) was registered in the first five days after the U.S. Congress approved the TARP bailout.

We use a calibrated dynamic asset pricing model with crash risk to study the impact of sector-wide bailout guarantees on individual and index option prices. In particular, we use a version of the Barro (2006) and Rietz (1988) asset pricing model with a time-varying probability of rare disasters. Our model features both Gaussian and financial disaster risk.[3] Our structural option pricing model without the bailout guarantee nests the workhorse Black-Scholes option pricing models as well as other option pricing models with fat-tailed return processes (e.g. Bates, 1991).

In our model, the collective government guarantee bounds the aggregate equity loss rate for the financial sector in a disaster, but not for individual firms in the sector. We model the financial crisis as an increased probability of a financial disaster. First, we show that a version of this (state-of-the-art) structural model without bailout guarantees cannot explain the joint stock and option moments for the financial sector that we document. It has the same defect as the much simpler Gaussian model sketched above, in that it predicts a decrease in the correlation between stock returns at the parameter values that generate an increased put spread. Second, we show that a model with a bailout guarantee can account for the facts, including the large decrease in the implied volatility skew for index put options compared to individual options. We estimate a reduction in the average loss rate for shareholders during financial disasters from 55.7 to 37.2 percent of equity. Third, we use the structural parameters of our model to infer the effect of the bailout option on financial firms' cost of capital. The downside protection lowers the equity risk premium in the financial sector by 50 percent. The collective bailout guarantee accounts for half of the value of the financial sector according to our model estimates. Fourth, we show robust results with respect to various aspects of the model.

We investigate and rule out three other potential alternative explanations for the sharp rise in the basket-index spread during the crisis. We consider mispricing due to capital constraints, counter-party risk, and short sale restrictions. A trade that takes advantage of the basket-index spread does not tie up capital and occurs through exchanges with a AAA-rated clearing house in

[3] Financial disasters are more frequent but smaller than the consumption disasters in Barro (2006).

the middle. The short sale ban was in place only for a very short time, applied equally to individual and index options, and market makers were exempted from it. We study liquidity differences among different types of options (index versus individual, puts versus calls, or financial firms versus non-financials), and argue that several of the facts are inconsistent with a liquidity explanation. Third, we consider and rule out a decline (in absolute value) in the price of correlation risk.

Our paper contributes to the growing literature on tail risk measurement and how this risk is priced. In recent work, Kelly (2011) uses the cross-section of stock returns to construct a measure of aggregate tail risk. Backus, Chernov, and Martin (2011) use option prices to make inference about the size and frequency of consumption disasters. Drechsler and Yaron (2011) study stock returns and option prices in a long-run risk model with jumps. Our work uses the relative valuation of sector and stock-specific option prices to distinguish between firm-specific and aggregate tail risk. We find that there was less aggregate tail risk priced in index option markets during the crisis than there would have been absent a bailout option.

Our paper also contributes to the options literature that studies the relationship between individual and index options. Driessen, Maenhout, and Vilkov (2009) argue that index options provide a hedge against increases in correlations, which constitute a deterioration in the investment opportunity set, because their prices rise when correlations increase. Individual options do not have this feature. That is what typically makes index options expensive. We show that index put options in the financial sector are relatively cheap during the crisis because they are essentially subsidized through the government guarantee. Carr and Wu (2009) and Schurhoff and Ziegler (2011) also study the price of index versus individual options. In earlier work, Bates (1991) uses OTM put and call index option prices to study the market's expectations about the 1987 stock market crash.

Other studies have measured the effect of guarantees on the cost of bank credit. Giglio (2010) and Longstaff, Arora, and Gandhi (2009) infer joint default probabilities for banks from the pricing of counter-party risk in credit default swap markets. Recently, Coval, Jurek, and Stafford (2009) and Collin-Dufresne, Goldstein, and Yang (2010) compare the prices of index options and CDX tranches prior and during the financial crisis. Veronesi and Zingales (2010) study the value of government bailouts to bondholders and stockholders of the largest financial firms during the crisis. We focus exclusively on the equity side, and we find evidence of a large collective equity bailout guarantee in the financial sector. From our model, we conclude that option prices tell us that the bailout option substantially reduces the cost of capital for systemically risky financial firms. Consistent with this result, Gandhi and Lustig (2010) quantify the effect of too-big-to-fail on the cost of equity capital of large banks by analyzing stock returns on size-sorted bank portfolios. They find that large banks have risk-adjusted returns that are 5% per annum lower than those of the smallest banks, and they attribute this difference to the implicit guarantee for large banks. In a seminal paper on this topic, O'Hara and Shaw (1990) document 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. Since we find strong evidence of ex-ante subsidies to shareholders, this implies that there are even larger subsidies to other creditors of large banks.

The rest of the paper is organized as follows. After defining index and basket put and call spreads and their relationship in Section 2, we document their empirical behavior in the financial sector and in all other non-financial sectors in Section 3. Section 4 finds supporting evidence for our collective bailout hypothesis in the events of the 2007-2009 crisis. Section 5 develops a structural asset pricing model which features a time-varying probability of financial disasters. A technical contribution of the paper is to derive option prices in the presence of a bailout option essentially in closed-form. Section 6 calibrates the model and shows that it is able to account for the observed option and return data, but only when a bailout guarantee is present. Section 7 studies and rules out three potential alternative explanations: mispricing, liquidity, and fluctuations in the price of correlation risk. The last section concludes. Technical details are relegated to a separate appendix.

2 Prices of Index Options Versus Option Baskets

Two potential ways to insure equity in the financial sector are 1) insuring each financial institution or 2) insuring the financial index. In this section we propose a comparison of these two insurance schemes that is useful for identifying investors' perceptions of government guarantees.

We focus on a traded sector index i comprised of different stocks j. $Index$ denotes the share price level of the index, which is a constant fraction $1/scale$ of the total market value of its constituent stocks. The dollar cost of the index, i.e., the total market cap of all the firms in the index, is given by $Index^{\$} = \sum_{j=1}^{N_i} s_j S_j$, where N_i is the number of different stocks that constitute index i, while S_j and s_j are the price per share and number of shares outstanding, respectively, for stock j in index i. This defines $scale = \frac{Index^{\$}}{Index}$. We use Put_i^{basket} to denote the price of a basket of put options on all stocks: $Put_i^{basket} = \sum_{j=1}^{N_i} s_j Put_j$. We use Put_i^{index} to denote the price of a put option on the sector index. Similarly, we use $Call_i^{basket}$ to denote the price of a basket of call options on all stocks in the sector index and $Call_i^{index}$ to denote the price of a call option on the index. We study two different ways of comparing basket and index options.

Δ-Matched Basket The first approach ensures that the index and the individual options have the same option Δ.[4] First, we choose strike prices K_j ($j = 1, 2, \ldots, N_i$) for individual stocks to match the targeted Δ level. Second, we choose the strike price K for the index to match that same Δ. Third, we choose the number of index options with strike K such that the total dollar amount insured by the index (denoted $K^{index,\$}$) is equal to the dollar amount insured by the basket:

$$K^{index,\$} = \sum_{j=1}^{N_i} s_j K_j.$$

The advantage of this approach is that both the index and individual options in the basket have the same moneyness. However, no-arbitrage does not bound the basket-index spread at zero from below.

Strike-Matched Basket The second approach ensures that the strike price on the index matches the share-weighted strike of the basket. First, we choose all the strike prices K_j ($j = 1, 2, \ldots, N_i$) for individual stocks that are part of the index to match a certain Δ. Second, we choose the strike

[4] The Δ of an option is the derivative of the option price with respect to the underlying asset price. While put options have negative Δ, we use the convention of taking the absolute value, so that all Δs are positive. Δ measures the moneyness of an option, with low values such as 20 indicating OTM options and high values such as 80 indicating in-the-money (ITM) options. At the money options have a Δ of 50.

price of the index options $K^{index,\$}$ (in billions) such that the strike price of the index (in dollars) equals the share-weighted sum of the individual strike prices:

$$K^{index,\$} = \sum_{j=1}^{N_i} s_j K_j.$$

Third, we choose a strike price for the index K such that the total dollar cost of insurance equals $K^{index,\$}$:

$$K^{index,\$} = K \times scale.$$

The advantage of this approach is that the cost of the basket has to exceed the cost of the index option by no arbitrage, which bounds the basket-index spread below from zero. The disadvantages are that the Δ of the index option can differ from the moneyness of the option basket and that this approach is computationally more involved.[5]

No-Arbitrage Basket-Index Relationship We compare the cost of the index option and the basket of options under the second approach. At expiration T, the payoff of the basket of options is: $Put_{T,i}^{basket} = \sum_{j=1}^{N_i} s_j \max(K_j - S_{T,j}, 0)$. We can compare this payoff to the payoff from the index put option: $scale \times Put_{T,i}^{index} = \max(K^{index,\$} - \sum_{j=1}^{N_i} s_j S_{T,j}, 0)$, where the strike price of the index in dollars is the weighted strike price of the underlying stocks in the basket $K^{index,\$} = \sum_{j=1}^{N_i} s_j K_j$.

Proposition 1. *The cost of the basket of put options has to exceed the cost of the index put option:*

$$Put_{t,i}^{basket} \geq scale \times Put_{t,i}^{index}, \forall t \leq T. \tag{1}$$

Proof. The payoffs at maturity satisfy the following inequality: $\sum_{j=1}^{N_i} s_j \max(K_j - S_{T,j}, 0) \geq \max(K^{index,\$} - \sum_{j=1}^{N_i} s_j S_{T,j}, 0)$. First note that, for each j, $s_j \max(K_j - S_{T,j}, 0) \geq s_j(K_j - S_{T,j})$. This implies that $\sum_{j=1}^{N_i} s_j \max(K_j - S_{T,j}, 0) \geq K^{index,\$} - \sum_{j=1}^{N_i} s_j S_{T,j}$. However, this also means that $\sum_{j=1}^{N_i} s_j \max(K_j - S_{T,j}, 0) \geq \max(K^{index,\$} - \sum_{j=1}^{N_i} s_j S_{T,j}, 0)$, because the left hand side is non-

[5] Since data are on a discrete grid of Δs, different option Δs can satisfy this condition on consecutive days. To avoid oscillation in the basket price, we set a given sector's basket Δ equal to the mode of the day-by-day best Δ match for that sector.

negative. Since the payoff from the option basket exceeds that of the index option, its cost must be weakly higher as well. □

Intuitively, the basket of put options provides insurance against states of the world in which there are large declines in the price of any individual stock, including declines that affect many stocks simultaneously. The index put option only provides insurance in those states of the world that prompt common declines in stock prices. The difference $Put_{T,i}^{basket} - Put_{T,i}^{index}$ between these two put prices is the cost of insurance against large declines in individual stock prices but not in the overall index. Hence, the basket-index spread is non-negative. The same inequality applies to the basket of calls and the call on the index.[6]

Cost Per Dollar Insured To compare prices across time, sectors, and between puts and calls, we define the cost per dollar insured (cdi) as the ratio of the price of the basket/index option divided by its strike price: $Put_{cdi,i}^{basket} = \frac{Put_i^{basket}}{\sum_{j=1}^{N_i} s_j K_j}$ and $Put_{cdi,i}^{index} = \frac{scale \times Put_i^{index}}{\sum_{j=1}^{N_i} s_j K_j}$. From equation (1), we know that the cost of basket insurance exceeds the cost of index insurance, $Put_{cdi,i}^{basket} \geq Put_{cdi,i}^{index}$, if we construct the index strike to match the share-weighted strike price. We define the basket-index put spread per dollar insured as: $Put_i^{spread} = Put_{cdi,i}^{basket} - Put_{cdi,i}^{index}$. $Call_{cdi,i}^{basket}$ and $Call_i^{spread}$ are defined analogously.

3 The Basket-Index Spread in the Data

This section documents our main stylized facts.

3.1 Data

We use daily option data from January 1, 2003 until June 30, 2009. Index option prices are on the nine SPDR[7] sector exchange-traded funds (ETFs) and on the S&P500 ETF, traded on the

[6] This property is unique to equity options. In the case of credit default swaps, the cost of a basket of credit default swaps has to be equal to the CDX index to rule out arbitrage opportunities.

[7] SPDRs are a large family of ETFs traded in the United States, Europe, and Asia-Pacific and managed by State Street Global Advisors.

CBOE. As ETFs trade like stocks, options on these products are similar to options on individual stock. Options on ETFs are physically settled and have an American-style exercise feature. The nine sector ETFs have the nice feature that they have no overlap and collectively cover the entire S&P500. Appendix A contains more details and lists the top 40 holdings in the financial sector ETF.[8] We also use individual option data for all 500 stocks in the S&P500. The OptionMetrics Volatility Surface provides daily European put and call option prices that have been interpolated over a grid of time-to-maturity (TTM) and option Δ, and that perform a standard adjustment to account for the American option feature of the raw option data. The European style of the resulting prices allows us to compare them to the options we compute in our structural model later. Interpolated prices allow us to hold maturity and moneyness constant over time and across underlyings. The constant maturity options are available at various intervals between 30 and 730 days and at grid points for (absolute) Δ ranging from 20 to 80. We focus primarily on options with 365 days to maturity and Δ of 20. Implied volatility data are from the interpolated implied volatility surface of OptionMetrics. We use CRSP for returns, market capitalization, and number of outstanding shares for sector ETFs and individual stocks. We calculate realized volatility of index and individual stock returns, as well as correlations between individual stock returns from CRSP return data. Our database changes as the index composition of the S&P500 changes. Whenever a firms gets added or deleted from the S&P500 and hence from its sector ETFs, we also drop it from the individual option data base so as to maintain consistency between the composition of the option basket and the index option.[9]

3.2 Δ-Matched Basket

This section describes the moments in the data for the basket-index option spread. We find that OTM put options on the index were cheap during the financial crisis relative to the individual stock options, while OTM index calls were relatively expensive. This pattern is much more pronounced

[8] Our sample length is constrained by the availability of ETF option data. For the financial sector (but not for all non-financial 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, do not materially change if we start in 1999.

[9] Our results remain unchanged when we focus on the subset of firms that remain in the financial sector index throughout our sample.

for the financial sector than for other non-financial sectors.

Panel I in Table I provides summary statistics for the basket-index spread per dollar insured for the Δ-matched approach using index and individual options with $\Delta = 20$. Columns (1)-(2) report results for the financial sector. Columns (3)-(4) report results for a value-weighted average of the eight non-financial sectors. Columns (5)-(6) report the differences in the spread between the financial and non-financial sectors. All spreads are reported in cents per dollar insured. An increase in the spread between the basket and the index means index options become cheaper relative to the individual options. We report statistics for three samples: the entire sample (top panel, January 2003 until June 2009), the pre-crisis sample (middle panel, January 2003 until July 2007), and the crisis sample (bottom panel, August 2007 until June 2009).

Over the full sample, the mean spread for OTM puts is 1.69 cents per dollar in the financial sector and 1.11 cents in the non-financial sectors. The basket-index spread for OTM calls are an order of magnitude smaller than those for puts: 0.24 cents for financials and 0.21 cents for non-financials. Put spreads are more volatile than call spreads: The standard deviation of the basket-index spread over time is 1.89 cents for puts compared to only 0.16 cents for calls in the financial sector. The largest basket-index put spread for financials is 12.45 cents per dollar, recorded on March 6, 2009. It represents 70% of the cost of the index option on that day. On that same day, the difference between the spread for financials and non-financials peaks at 9.07 cents per dollar insured. The largest put-based basket-index spread for non-financials is 4.1 cents per dollar, recorded on November 21, 2008. In contrast, the largest basket-index call spread is only 0.49 cents for financials and 0.36 cents for non-financials.

The bottom half of Panel I focuses on the crisis subsample. The mean spread backed out from OTM puts is 3.79 cents per dollar for financials and 1.57 for non-financials. While there is an across-the-board increase in the put spread from pre-crisis to crisis, the increase is much more pronounced for financials (4.7 times versus 1.7 times). Put spread volatility increases in the crisis, especially for financials, whose standard deviation rises from 0.20 pre-crisis to 2.39 during the crisis. Non-financial put spread volatilities increase from 0.44 to only 0.90. A very different pattern emerges for OTM call spreads. They are substantially lower in the crisis than in the pre-crisis period. The crisis call spread is 0.06 cents for financials and 0.11 cents for non-financials. The volatility increases only modestly from 0.06 to 0.17 (0.05 to 0.10) for financials (non-financials).

Figure 2 plots the cost of the basket of put options per dollar insured (full line), the cost of the financial sector put index (dashed line), and the basket-index spread (dotted line) for the entire sample. Before the crisis, the basket-index spread is essentially constant and very small, less than 1 cent per dollar. During the crisis, the put spread increases as the index option gradually becomes cheaper relative to the basket of put options. The cost of the basket occasionally exceeds 30 cents while the cost of the index put rarely rises above 20 cents per dollar. At the start of 2009, the difference exceeds 12 cents per dollar of insurance. The basket index spread also becomes more volatile. By fixing Δ as the crisis unfolds, we are looking at put contracts with lower strike prices during the crisis, and hence at options with lower prices. This tends to lower the basket-index spreads. None of the eight non-financial sectors has anywhere close to such a large put spread increase during the crisis.

Figure 2 plots the cost per dollar insured of basket and index call options, as well as the call spread. During the crisis, index options become more expensive relative to the basket of call options. In addition, the volatility of the basket-index spread decreases. At some point, the call spread becomes negative (-0.44 cents at the lowest point).[10] We find essentially the same results for call spreads in all other sectors.

Figure 3 compares the put spread of financials and non-financials over time (the dotted lines from the previous two figures). For non-financials (solid line), the basket-index spread remains very low until the Fall of 2008. For financials (dashed line) on the other hand, the put spread starts to widen in the summer of 2007 (the asset-backed commercial paper crisis), spikes in March 2008 (the collapse of Bear Stearns), and then spikes further after the Freddie Mac and Fannie Mae bailouts and the Lehman Brothers bankruptcy in September 2008. After a decline in November and December of 2008, the basket-index spread peaks at 12 cents per dollar in March 2009. The dotted line plots the difference in put spread between the financial sector and non-financial sectors. This

[10] Recall that the zero lower bound for the spread only holds for strike-matched and not Δ-matched options, so that this negative number does not present a puzzle.

difference is positive throughout the crisis, except for a few days in November of 2008. It increases from the summer of 2007 to October 2008, falls until the end of 2008, and increases dramatically from January to March 2009. Section 4 provides a detailed interpretation of this pattern based on crisis-related government announcements.

Different Sectors Table II compares the basket-index spread for different sectors. The only two industries which experienced large increases in the basket-index spreads during the crisis were the consumer discretionary sector and the materials sector. The consumer discretionary sector was highly exposed to aggregate tail risk. Discretionary spending of U.S. consumers experienced the largest post-war decrease during the last quarter of 2008. One major component of this sector is car manufacturers (Ford and GM) and parts suppliers (e.g., Goodyear and Johnson Controls), but it also includes retail, home construction (e.g., D. R. Horton and KB Home), hotels (e.g., Marriott and Harrah's) and other businesses with substantial direct and indirect real estate exposure. The basket-index spread peaked at 9 cents per dollar insured for this industry. The average increased from 1.84 cents to 3.28 cents per dollar insured. It is conceivable that this sector would benefit more than other sectors when the collective guarantee for banks kicks in. In fact, the auto industry benefited directly from a federal government bailout. The materials sector ETF has similarly large exposure to businesses benefitting from government guarantees. Examples include US Steel, whose large customers include the transportation and construction industries, and Weyerhaeuser, which produces building materials and operates a large real estate development segment.

3.3 Strike-Matched Baskets

Panel II in Table I reports results for our second approach to compare basket-index spreads: the index strike matches the share-weighted strike price of the basket. In this case, no-arbitrage implies that the basket-index spreads are non-negative. Essentially, we see the same pattern as with the Δ-matching approach. The correlation between these two measures is 0.995. However, the basket-index spreads are larger when we match the share-weighted strike price. The reason is that the higher volatility of individual stock returns leads to a lower (higher) strike price for OTM put (call) options when we match Δs. Put differently, individual options in the second approach have higher Δs than index options, which increases spreads.

The average put spread during the crisis is 5.85 cents per dollar for financials (compared to 3.79 cents in Panel I), and the volatility is 3.01 (compared to 2.39). The maximum spread is now 15.87 cents per dollar insured (compared to 12.46). This number represents 89% of the cost of the index put on March 6, 2009 (compared to 70%). On that same day, the difference between the put spread for financials and non-financials peaks at 10.17 cents per dollar. The maximum spread for calls is only 1.27 cents per dollar. The minimums reported are all positive, which means the no-arbitrage constraint is satisfied. Since our results do not seem sensitive to how we perform the basket-index comparison, we report only the Δ-matched basket-index spread results in the remainder of the paper.

3.4 The Effect of Time To Maturity

Panel III of Table I studies the cost of insurance when the TTM is 30 days instead of 365 days. As we show later, these shorter maturity option contracts are more liquid. Naturally, all basket-index spreads are smaller for shorter-dated options, because the cost per dollar insured increases with the TTM. Yet, we observe the same patterns as in Panel I. We limit our discussion to Panel III; the strike-matched results in Panel IV are very similar.

Starting with the basket-index spread for puts on financials, we find an average of 0.62 cents per dollar in the crisis, up from 0.17 cents pre-crisis. This represents an increase by a factor of 3.7, only slightly lower than the 4.7 factor with $TTM = 365$. Per unit of time (that is, relative to the ratio of the square root of maturities), the put spread increase during the crisis is larger for $TTM = 30$ options than for $TTM = 365$ options. The 30 day spread reaches a maximum of 2.46 cents per dollar or 52% of the cost of the index option on that day. The call spread for financials decreases from an average of 0.16 cents pre-crisis to an average of 0.10 cents during the crisis, a slower rate than for longer-dated options. For non-financials, there is an increase in the put spread by a factor of 1.8 (from 0.13 before the crisis to 0.23 cents during the crisis). This is similar to the increase in long-dated puts of 1.8 times, and larger when taking into account the shorter time interval. The call spread for non-financials increases slightly during the crisis (from 0.11 to 0.14 cents), while it falls for longer-dated options (from 0.25 to 0.11 cents). This is the only qualitative (but quantitatively small) difference with longer-dated options.

3.5 The Effect of Moneyness

Table III reports the cost of insurance for the basket versus the index as a function of moneyness (Δ). It follows the format of Table I, and their first panel is identical. While option prices are naturally higher when options are closer to being in the money (ITM), it turns out that spreads also increase in size. However, the proportional increase in the basket-index spread from pre-crisis to crisis is much larger for OTM put options than for at-the-money (ATM) puts.

Starting with financials, options with the lowest moneyness ($\Delta = 20$) see the largest proportional increase in put spread from pre-crisis to crisis. That factor is 4.7 for $\Delta = 20$, 3.5 for $\Delta = 30$, 3.0 for $\Delta = 40$, and 2.5 for ATM options ($\Delta = 50$). Similarly, the proportional decrease in call spreads is larger for OTM than for ATM options. For non-financials, the put spread increase during the crisis is much smaller and decreases in moneyness. The difference in the put spread between financials and non-financials (reported in column 5) increases only marginally during the crisis, from 2.22 cents at $\Delta = 20$ to 2.37 cents per dollar at $\Delta = 50$. Since ATM option prices are obviously higher for high-Δ options, the financials minus non-financials put spreads are much larger in percentage terms for OTM options. To illuminate this point, Table IV reports the percentage spread, measured as the basket-index spread divided by the cost of the index option. For put options on financials, the percentage spread during the crisis is 37% for $\Delta = 20$ but only by 26% for $\Delta = 50$. Similarly, the maximum percentage put spread falls from 81% to 52% as moneyness increases. For call options on financials, the largest percentage spreads are in the pre-crisis sample. Finally, we only see large increases in the average percentage spreads for OTM put options with $\Delta = 20$ on financials.

3.6 Correlation and Volatility

The crisis was characterized by a substantial increase in the correlation of individual stock returns. Panel I of Tables VI and VIII reports the average pairwise correlations for financials and non-financials stocks, respectively, computed from daily return data. Correlation among stocks in the financial sector index is 51.3% on average over the entire sample. This number increased from 45.8% pre-crisis to 57.6% during the crisis. For non-financials, the correlations are lower. The average correlation is 45.2%. This number increased from 33.7% pre-crisis to 56.8% in the crisis. Figure 4 plots correlations for financials and non-financials. The correlations for financials are invariably higher. We argue below that the increase in correlations during the crisis is evidence that points towards the collective bailout hypothesis.

Panel I of Tables VI and VIII also reports realized volatility of individual stock and index returns for financials and non-financials. Panel I of Tables V and VII reports option-implied volatilities in financials and non-financials. Over the entire sample, the implied volatility is 2.9 percentage points higher than the realized volatility for financials. In the pre-crisis sample, this difference is 9.8 percentage points (21.7% versus 11.9%). However, in the crisis-sample, this difference shrinks to 4.7 percentage points (48.5% versus 43.8%). The ratio of the two falls from 1.8 to 1.1. In the options literature, the difference between implied volatility and the expectation of realized volatility is called the volatility risk premium. To the extent that the sample realized volatility is a good proxy of the conditional expectation of realized volatility, this is evidence that the volatility risk premium in financials decreases during the crisis.[11] It is yet another important indication that index put options on the financial sector are cheap during the crisis. For non-financials, in contrast, the volatility risk premium barely decreases during the crisis. The difference between implied volatility and average realized volatility is 9.5 percentage points in the pre-crisis sample compared to 9.1 percentage points during the crisis. Similarly to puts, call options on financials indicate a large decrease in the volatility risk premium from 3.0 percentage points to -6.0 percentage points in the crisis. The decrease is again smaller for non-financials.

[11] In any GARCH model, lagged volatility is the key predictor of future volatility.

Bending the Implied Volatility Skew The government effectively bends the implied volatility skew for index put options, much more than for individual options, in the financial sector. As is clear from Figure 5, the average implied volatility difference between the basket and the index is higher for deep out-of-the-money put options during the crisis. The difference between the implied volatility of the basket and that of the index reaches a maximum of 11.5% for $\Delta = 20$, and gradually decreases to 9% for $\Delta = 50$. This downward sloping pattern arises because a government guarantee has a larger relative impact on put prices with lower strike prices. In the pre-crisis sample, the basket-index skew spread in implied volatility was essentially flat across moneyness. The same applies for the basket-index spread in the other sectors, both pre-crisis and during the crisis. Finally, Figure 6 plots the implied vol spread inferred from calls. Here we see the exact opposite pattern. During the crisis, the basket-index implied volatility difference for calls actually has a positive slope. This is because OTM index call options were substantially more expensive than the basket, while the prices of ATM index calls were much closer to the basket price. This is consistent with elevated aggregate tail risk during the crisis and high return correlations, exactly what we would expect to see (including for puts) in the absence of a bailout guarantee.

4 The Basket-Index Spread and the Government

In this section, we provide direct evidence that the dynamics of the basket-index spread during the crisis are closely tied to government announcements that relate directly to the collective bailout hypothesis. In a financial disaster, the banking sector is insolvent because the sector's asset value drops below the value of all debt issued. Under the collective bailout hypothesis, the government bounds the value of total losses to equity holders in a financial disaster. In principle, bailouts of bondholders and other creditors do not imply that the value of equity is protected. However, in practice, given the uncertainty about the resolution regime, especially for large financial institutions, the collective bailout ensures a positive value of equity in the financial sector. In the presence of a collective bailout guarantee, an increase in the probability of a financial disaster increases the put basket-index spread because the cost of downside insurance for the entire sector, which is supported by the government, increases by less than the cost of downside insurance for all the stocks in the basket. If the guarantee is specific to the financial sector, we do not expect to see the same pattern in other sectors.

To link the put spread directly to (the market's perceptions of) the government's bailout actions, we study government announcements during the financial crisis of 2007-2009. We focus on significant announcements for which we can determine ex-ante the sign of the effect on the likelihood (and size) of a collective bailout.

Announcement Effects We identify five events that increase the probability of a government bailout for shareholders of the financial sector: (i) October 3, 2008: Revised bailout plan (TARP) passes the U.S. House of Representatives, (ii) October 6, 2008: The Term Auction Facility is increased to $900bn, (iii) November 25, 2008: The Term Asset-Backed Securities Loan Facility (TALF) is announced, (iv) January 16, 2009: Treasury, Federal Reserve, and the FDIC Provide assistance to Bank of America, (v) February 2, 2009: The Federal Reserve announces it is prepared to increase TALF to $1trn. We refer to these as positive announcement dates. These announcement dates are indicated in the top panel of Figure 7, which plots the basket-index spread.

We also identify six negative announcements that (we expect ex-ante to) decrease the probability of a bailout for shareholders: (i) March 3, 2008: Bear Stearns is bought for $2 per share, (ii) September 15, 2008: Lehman Brothers files for bankruptcy, (iii) September 29, 2008: House votes no on the bailout plan, (iv) October 14, 2008: Treasury announces $250bn capital injections, (v) November 7, 2008: President Bush warns against too much government intervention in the financial sector, and (vi) November 13, 2008: Paulson indicates that TARP will not used for buying troubled assets from banks. These announcement dates are depicted against the basket-index spread in the bottom panel of Figure 7.

Figure 8 plots the basket-index put spread for financials around the announcement dates. The panel on the left shows the five positive announcements (dashed lines), while the panel on the right shows the six negative announcements (dashed lines). The solid line depicts the average effect across events. We find that the basket-index spread increases 1.61 cents (27%) in the first 5 days following a positive announcement, while it decreases 0.85 cent (13%) in the first 5 days following a negative announcement, on average across announcements. The pre-announcement movements suggest that some are anticipated by the market.

We obtain similar average responses when we examine the financial minus the non-financial basket-index spread around announcement dates instead. Figure 9 plots the basket-index spread of financials less that of non-financials around the same events. The basket-index spread increases 0.82 cents (24%) in the first 5 days following a positive announcement, while it decreases 0.93 cents (23%) in the first 5 days following a negative announcement. Hence, these announcement dates mainly affect the financial spread not the non-financial spread.

The largest positive effect occurs after the House approves the Emergency Economic Stabilization Act of 2008 (Public Law 110-343) on October 3, which establishes the $700 billion Troubled Asset Relief Program (TARP). The spread increases 3 cents or 60% in the first five days after the announcement. Furthermore, the approval of TARP started a sustained increase in the basket-index spread in the ensuing period.

Both the failure of Bear Stearns and Lehman Brothers initially reduce the basket-index put spread. In the case of the Lehman failure, the spread goes back up in the following days. Possibly, the government underestimated the consequences of the failure and markets subsequently increased the perceived probability of a bailout. The largest negative effect was registered on October 14, when the U.S. Treasury announced the TARP would be used as a facility to purchase up to $250bn in preferred stock of U.S. financial institutions. The Treasury essentially shifted TARP's focus from purchasing toxic assets to recapitalizing banks which resulted in dilutions of existing shareholders. As a result, the put spread declined about 2.5 cents per dollar insured (about 35%) in the first five days after the announcement.[12]

This decline in the spread was reversed only in early January when the FDIC, the Fed and the Treasury provided assistance to Bank of America, without diluting existing shareholders. The put spread started its largest increase in the beginning of February 2009 and peaked in the beginning

[12] This announcement started a major decline in the spread that was reinforced by speeches delivered by president Bush and Secretary Paulson in early November. Clearly, there was a fear that bank shareholders would not receive the government bailout they had hoped for.

of March.[13]

Markets were gradually reassured that the government was indeed committed to bailing out the financial sector without wiping out equity holders. Our measure of the value of the bailout guarantee suggests that the market was not initially reassured by the TARP program and its implementation, which consisted mostly of cash infusions from sales of preferred shares. Only when the Treasury and the Federal Reserve explicitly announce programs to purchase toxic assets such as mortgage-backed securities does the collective bailout guarantee become valuable.

Non-financials During the financial crisis, as market-wide volatility increased, index put options on non-financials also became cheaper relative to individual stock options. The non-financials put spread (dotted line in Figure 7) hovers around 1 cent until Lehman Brothers fails in September 2008. After that, it increases to 3.9 cents on October 10, and it reaches a maximum of 4.1 cents on November 21. This suggests that, for a brief period, the market was expecting bailouts in certain non-financial sectors as well.[14] Nevertheless, the magnitude of the put spread in non-financials is much smaller than in financials.

5 Model with Financial Disaster Risk

There are several reasons why a structural model is essential to interpreting the evidence presented thus far. It is well known that financial risks fluctuate over time, sometimes dramatically. Persistent fluctuations in return volatility have been considered a central feature asset markets since at

[13]On February 10, 2009, Treasury Secretary Geithner announced a Financial Stability Plan involving Treasury purchases of convertible preferred stock in eligible banks, the creation of a Public-Private Investment Fund to acquire troubled loans and other assets from financial institutions, expansion of the Federal Reserve's Term Asset-Backed Securities Loan Facility (TALF), and new initiatives to stem residential mortgage foreclosures and to support small business lending. The Federal Reserve Board announced that it was prepared to expand TALF to as much as $1trn and to broaden eligible collateral to include AAA-rated commercial mortgage-backed securities, private-label residential mortgage-backed securities, and other asset-backed securities. The expansion of TALF would be supported by $100bn from TARP. In the last week of February there was discussion of assurances to prop up the banking system, including Fannie Mae and Freddie Mac.

[14]For example, on November 18, the CEOs of General Motors, Chrysler, and Ford testify before Congress and request access to TARP for federal loans. This access is granted on December 19, 2008. As we discussed above, the consumers discretionary and materials sectors, which contain car manufacturers and homebuilders, experienced the largest increase in put spread among all non-financial sectors.

least the work of Bollerslev, Engle, and Wooldridge (1988). Time series dynamics in skewness (see Harvey and Siddique, 1999), jump risk (see Chan and Maheu, 2002) and tail risk (see Kelly, 2011) of equity returns have also been documented. Because these features have a first order impact on option prices (and therefore on the basket-index spread), an option pricing model is necessary to disentangle the effects of risk fluctuations from those of bailout guarantees. Furthermore, to ensure that we are capturing the effects of government guarantees rather than model misspecification, we work with state-of-the-art modeling tools that have demonstrated success in describing options prices (see Broadie, Chernov, and Johannes, 2007, 2009). These tools capture the aforementioned properties (volatility fluctuations, asymmetries, and tail risks) that are now considered essential ingredients of accurate option pricing (Bates, 2003). Finally, in order to back out the effects of the guarantee on the cost of capital of financial institutions and their market value, we embed a these building blocks in a fully specified macro-finance dynamic asset pricing model.

The critical difference between banks and other non-financial corporations is their susceptibility to bank runs during financial crises. Historically, runs have been made by depositors, but in the modern financial system they are made by other creditors such as investors in asset-backed commercial paper, repos, and money market mutual funds (see Gorton and Metrick, 2009). This leads us to consider banking panics or financial disasters as a source of aggregate risk. To model the asset pricing impact of financial disasters, we use a version of the Barro (2006), Rietz (1988) and Longstaff and Piazzesi (2004) asset pricing models with a time-varying probability of disasters, as developed by Gabaix (2008), Wachter (2008) and Gourio (2008). The model features two sources of priced risk: Gaussian risk and financial disaster (tail) risk. While non-financial corporations are also subject to financial crises, their exposure is more limited and they do not (or at least much less) enjoy the collective bailout guarantee that supports the financial sector.

We first describe the model environment and solve for equilibrium prices. A technical contribution of the paper is to derive analytical option pricing expressions in such a setting with bailout guarantees. We then compare the calibrated model to the empirical evidence documented above.

5.1 Environment

Preferences We consider a representative agent with Epstein and Zin (1989) preferences over non-durable consumption flows. For any asset return $R_{i,t+1}$, this agent faces the standard Euler equation:

$$\begin{aligned} 1 &= E_t\left[M_{t+1}R_{i,t+1}\right], \\ M_{t+1} &= \beta^{\alpha}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\alpha}{\psi}} R_{a,t+1}^{\alpha-1}, \end{aligned}$$

where $\alpha \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$, γ measures risk aversion, and ψ is the elasticity of inter-temporal substitution (EIS). The log of the stochastic discount factor (SDF) $m = \log(M)$ is given by:

$$m_{t+1} = \alpha \log \beta - \frac{\alpha}{\psi}\Delta c_{t+1} + (\alpha - 1) r_{a,t+1}.$$

All lowercase letters denote logs. We note and use later that $\frac{\alpha}{\psi} + 1 - \alpha = \gamma$.

Uncertainty There is a time-varying probability of disaster, p_t. This probability follows an I-state Markov chain. Let Π be the $1 \times I$ steady-state distribution of the Markov chain and $\mathcal{P}$ the $I \times 1$ grid with probability states. The mean disaster probability is $\Pi\mathcal{P}$. The Markov chain is uncorrelated with all other consumption and dividend growth shocks introduced below. However, the volatility of Gaussian consumption and dividend growth risk potentially varies with the Markov state. This allows us to capture higher Gaussian risk in bad states associated with high disaster probabilities.

In state $i \in \{1, 2, \ldots, I\}$, the consumption process (Δc_{t+1}) is given by a standard Gaussian component and a disaster risk component:

$$\Delta c_{t+1} = \begin{cases} \mu_c + \sigma_{ci}\eta_{t+1} & \text{if no disaster} \\ \mu_c + \sigma_{ci}\eta_{t+1} - J^c_{t+1} & \text{if disaster,} \end{cases}$$

where η is a standard normal random variable and J^c is a Poisson mixture of normals governing the size of the consumption drop (jump) in the disaster state. We adopt the Backus, Chernov, and Martin (2011) model of consumption disasters. The random variable J^c is a Poisson mixture of normal random variable. The number of jumps is n with probability $e^{-\omega}\frac{\omega^n}{n!}$. Conditional on n, J^c is normal with mean $(n\theta_c)$ and variance $n\delta_c^2$. Thus, the parameter ω (jump intensity) reflects the average number of jumps, θ_c the mean jump size, and δ_c the dispersion in jump size.[15] Finally, we allow for heteroscedasticity in the Gaussian component of consumption growth: σ_{ci} depends on the Markov state i.

Individual Dividends in Financial Sector In state $i \in \{1, 2, \ldots, I\}$, the dividend process of an individual bank is given by:

$$\Delta d_{t+1} = \begin{cases} \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1} & \text{if no disaster} \\ \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_{di} \epsilon_{t+1} - J^d_{t+1} - \lambda_d J^a_{t+1} & \text{if disaster} \end{cases}$$

where ϵ_{t+1} is standard normal and i.i.d. across time. It is the sum of an idiosyncratic and an aggregate component, which we introduce in the calibration below. The term $\exp(-J^d_{t+1} - \lambda_d J^a_{t+1})$ can be thought of as the recovery rate corresponding to a disaster event. The loss rate varies across banks. It has an idiosyncratic component J^d and a common component J^a. The parameter λ_d governs the exposure of the bank to aggregate tail risk. The idiosyncratic jump component is a Poisson mixture of normals that are i.i.d. across time and banks, but with common parameters $(\omega, \theta_d, \delta_d)$. We set $\theta_d = 0$, which implies that the idiosyncratic jump is truly idiosyncratic; during a disaster the average jump in any stock's log dividend growth is equal to the common component, $-\lambda_d E[J^a]$.[16]

Collective Bailout Option The key feature of the model is the presence of the collective bailout option which puts a floor $\underline{J}$ on the losses of the banking sector. The aggregate component of the loss

[15] Note that when J^c is activated, we have already conditioned on a disaster occurring. Therefore, the parameter ω is not the disaster frequency but rather the mean of the number of jumps, conditional on a disaster. There is a non-zero probability $e^{-\omega}$ of zero jumps in the disaster state. In what follows we normalize ω to 1.

[16] The cross-sectional mean of λ_d is 1.

rate is the minimum of the maximum industry-wide loss rate $\underline{J}$ and the actual realized aggregate loss rate J^r:

$$J^a_{t+1} = \min(J^r_{t+1}, \underline{J}).$$

We model J^r as a Poisson mixture of normals with parameters $(\omega, \theta_r, \delta_r)$. For simplicity, we assume that the jump intensity is perfectly correlated among the three jump processes (J^c, J^i, J^r), but the jump size distributions are independent. We can think of the no-bailout case as $\underline{J} \to +\infty$, so that $J^a = J^r$. We do not model the government budget constraint, but we note that the resources that are spent in providing this backstop can be financed by issuing government debt and do not have to reduce current aggregate consumption.

5.2 Valuing Stocks

In sections B.1 and B.2 of the separate appendix, we derive a system of equations that can be solved for the equilibrium log wealth-consumption ratio and price-dividend ratios, respectively. An important object is the equity risk premium, which is the expected excess log stock return (adjusted for a Jensen inequality term). This is equal to minus the covariance between the log SDF and asset return:

$$-Cov(m, r) \;=\; \gamma\phi_d\sigma^2_{ci} - \zeta_{m,i} + \gamma Cov(J^d 1_D, J^c 1_D) + \gamma\lambda_d Cov(J^a 1_D, J^c 1_D),$$

where 1_D is an indicator variable that is activated by the occurrence of a disaster. Appendix B.3 derives the right-hand-side terms as a function of the structural parameters. The first term represents the standard Gaussian equity risk premium, the second term reflects compensation for the risk that emanates from the Markov switches, while the third and fourth terms are compensation for disaster risk. The third term is zero by virtue of our normalization $\theta_d = 0$, so that the last term represents the entire disaster risk premium. It depends on the risk aversion coefficient, the probability of a disaster, and the extent to which aggregate consumption and financial stocks' dividends fall in a disaster. The latter depends on θ_r and λ_d as well as on the bailout guarantee,

$\underline{J}$. Absent the bailout guarantee, the disaster risk premium would be $\gamma\lambda_d p_i(2-p_i)\theta_c\theta_r$, which is always higher than the equity premium in the presence of a guarantee.

5.3 Valuing Options

The main technical contribution of the paper is to price options in the presence of a bailout guarantee.

Options on Individual Banks We are interested in the price per dollar invested in a put option (cost per dollar insured) on a bank stock. For simplicity, we assume that the option has a one-period maturity and has European exercise style. We denote the put price by Put:

$$Put_t = E_t\left[M_{t+1}\left(K-R_{t+1}\right)^+\right] = (1-p_t)Put_t^{ND} + p_t Put_t^{D},$$

where the strike price K is expressed as a fraction of a dollar (that is, $K=1$ is the ATM option). The put price is the sum of a disaster component and a non-disaster component. The no-disaster option price in state i:

$$Put_i^{ND} = \sum_{j=1}^{I}\pi_{i,j} Put_{ij}^{ND},$$

where Put_{ij}^{ND}, the option price conditional on a transition from i to j, has the familiar Black-Scholes form. Similarly, the disaster option price in state i:

$$Put_i^{D} = \sum_{j=1}^{I}\pi_{i,j}\sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}Put_{ijn}^{D}. \tag{2}$$

where Put_{ijn}^{D} is the option price conditional on a transition from i to j and n jumps. Because of the truncation of payoffs by the bailout, the valuation of these disaster options is non-standard. The closed-from expressions for option prices are provided in section B.4 of the separate appendix. We verify there that the above put price collapses to the simpler case of no bailout options, that is $J^a = J^r$. This is the case as $\underline{J} \to +\infty$.

Options on the Financial Sector To aggregate from the individual firms to the index, we use a generic set of index weights w_j ($j = 1, \cdots, N_i$) for the sector i's constituents, where $\sum_{j=1}^{J} w_j = 1$. We assume that all individual firms in an index face the same dividend growth parameters (thus they are ex-ante identical except for size w_j). Assuming in the model that all stocks initially trade at \$1, the one-period dividend growth rate of the index in the model is given by:

$$\Delta d^{index} \approx \sum_{j=1}^{J} w_j \Delta d^j.$$

The weights allow us to take into account a finite number of index constituents as well as sector concentration, as measured by $\sqrt{\sum w_j^2}$. The Gaussian dividend growth shock ϵ, which is not priced, has standard deviation σ_{di}. We assume that a fraction ξ_d of its variance is aggregate, with the remainder being idiosyncratic. It follows that the Gaussian variance of the index is given by

$$\sigma_{di}^{index} = \sigma_{di} \sqrt{\xi_d + \sum_{j=1}^{N_i} w_j^2 (1 - \xi_d)}.$$

The gains from diversification make the Gaussian variance of the index lower than that of its constituents. Similarly, the idiosyncratic tail risk of the financial sector index is much lower than that of any individual stock:

$$\delta_d^{index} = \delta_d \sqrt{\sum_{j=1}^{N_i} w_j^2}$$

and $\theta_d^{index} = \theta_d = 0$. The growth rate of the sector's dividends is then given by:

$$\begin{aligned}
\Delta d_{t+1}^a &= \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_d^{index} \epsilon_{t+1}, \quad \text{if no disaster} \\
\Delta d_{t+1}^a &= \mu_d + \phi_d \sigma_{ci} \eta_{t+1} + \sigma_d^{index} \epsilon_{t+1} - J_{t+1}^{d,index} - J_{t+1}^a, \quad \text{if disaster}
\end{aligned}$$

where we have assumed $\sum_{j=1}^{J} w_j \lambda_{d,j} = 1$. Since $J^{d,index}$ has mean zero, $\exp\left(-J_{t+1}^a\right)$ is the recovery rate of the index in case the rare event is realized.

6 Quantitative Model Predictions

The goal of this section is threefold. First, we argue that a (state-of-the-art) structural model with bailout guarantees can explain the pattern in option prices and stock returns we document in the previous section. Second, we show that a model without a bailout guarantee cannot. Third, we use the structural parameters of the model to infer the effect of the government guarantee on financial firms' expected return and stock price. We finish by showing robustness of our main conclusions to variations in the details of the model.

6.1 Parameter Choices

We calibrate the model at the annual frequency to match it with option prices of one-year maturity.

Disaster probabilities We set the number of Markov states I equal to 2 and treat the first state as the pre-crisis state and the second state as the crisis state. We think of the pre-crisis period (January 2003-July 2007) as a period of low probability of a financial disaster. We think of the crisis (August 2007-June 2009) as a period of elevated probability of a financial disaster (as well as the actual realization of a financial disaster). Since we want to match data for this particular 78 month period, we choose the elements of the transition probability matrix so that the Markov chain resides in a crisis 29.5% of the time (the same 23 out of 78 months as in the data). This leads us to set $\pi_{11} = .79$ and $\pi_{22} = .50$. We calibrate the steady-state probability of a financial disaster to a much longer time series. In particular, we match the 13% historical frequency of financial disasters in the U.S. since 1800 documented in Reinhart and Rogoff (2009). Given the Markov transitions and $p_{ss} = 13\%$, we set the probability of a financial disaster equal to 7% in state 1 and 28% in state 2 so as to have a big spread in probabilities.

Consumption We set μ_c equal to real per capita total consumption growth during the pre-crisis period, which is 2.21% in our sample. Coincidentally, that is also the average over the full 1951-2010 sample. Unconditional average consumption is $\mu_c - p_{ss}\theta_c$ in the model. We choose $\theta_c = .065$ to match average annual real consumption growth of 1.37% over our 2003-2009 sample. That means that annual consumption drops 4.3% (2.2%-6.5%) in real terms in a disaster. This consumption drop is close to the 5.9% annual consumption drop during a typical financial crisis in developed economies, as reported in Reinhart and Rogoff (2009).[17] We choose $\sigma_{c1} = .0035$ to match the standard deviation of real per capita consumption growth (annualized from overlapping quarterly data) of 0.35% in the pre-crisis period. We set $\delta_c = .035$ to allow for non-trivial dispersion around the size of the consumption disaster and we allow for a doubling of Gaussian consumption risk to $\sigma_{c2} = .0070$. This delivers an unconditional consumption growth volatility of 0.92% per year given all other parameters. This is close to the observed volatility of 0.81% in our sample and exactly matches the 0.92% in the 1951-2010 sample. Seen from the model's perspective and interpreting the period 2007-2009 as the realization of a disaster, the observed consumption growth rate of -0.7% (or 2.9% lower than in the non-disaster state) was one standard deviation above the mean growth rate in disasters.

Preferences We set the coefficient of relative risk aversion equal to 10 and the inter-temporal elasticity of substitution equal to 3. The combination of a high risk aversion and a high EIS allows us to simultaneously generate a meaningful equity risk premium and a low risk-free rate. The high risk aversion will also be necessary to match the high OTM put prices observed during the crisis. We set the subjective time discount factor $\beta = .9555$. The unconditional real risk-free rate that results is 2.44% per year. It is 3.43% in state 1 and 0.07% in state 2, reflecting the additional precautionary savings motive when a disaster is more likely. This compares to an observed average yield on a one-period zero coupon government bond of 0.66% in the pre-crisis period and 0.05% in the crisis period, after subtracting realized inflation.[18] The unconditional volatility of the risk-free rate is low at 1.54% per annum, matching the 1.59% volatility in our sample.

[17] Reinhart and Rogoff find that the (worldwide) average financial crisis is associated with a 35.5% fall in GDP over six years. Barro and Ursua (2008) find that consumption disasters are typically of the same magnitude as GDP contractions during crises.

[18] Lowering average interest rates, as well as the difference between the interest rates in state 1 and 2, is possible if we further increase the EIS, while simultaneously increasing the time discount factor. We opt not to do this because the EIS is already high. Furthermore, we need strictly positive interest rates in both states in order to be able to compute Black-Scholes implied volatilities for comparison with OptionMetrics data. Our parameter choices are a compromise that still delivers the low interest rate environment of our sample period.

Dividends Next, we calibrate the parameters that govern the dividend growth rate of the firms in the financial sector. The mean growth rate of any firm, and therefore of the index, is $\mu_d = .08$ in order to match the high observed dividend growth rate on the financial sector index in the pre-crisis period. We set $\phi_d = 3$, a standard choice for the leverage parameter. This delivers a negligible Gaussian equity risk premium ($\gamma\phi_d\sigma_c^2$) of four basis points in state 1 and 15 basis points in state 2. The equity risk premium in the model predominantly reflects compensation for disaster risk.

The key objects of the model are the parameters that govern Gaussian risk and, especially, tail risk. Sector risk depends in part on the degree of diversification in the sector. We therefore use a representative set of index weights for the financial sector index constituents (that of 04/09/2010, 79 firms on that day) for w_j where $\sum_{j=1}^{J} w_j = 1$. The concentration metric $\sqrt{\sum w_j^2}$ is 0.22 for the financial sector (on that day).[19] We keep σ_d constant across Markov states in our benchmark calibration for simplicity. We set $\omega = 1$, which implies that the average number of jumps during a disaster is one, $\theta_d = 0$, which implies that the idiosyncratic jump is truly idiosyncratic, and $\lambda_d = 1$, which implies that the average exposure to the aggregate tail risk process is one. These are innocent normalizations. The parameters that remain to be calibrated are $\Theta = (\sigma_d, \xi_d, \underline{J}, \theta_r, \delta_r, \delta_d)$. Together these parameters determine the equity risk premium, the volatility of dividend growth and returns at the individual and index level, the pairwise correlation between stock returns, and all option prices. It is the parameters in Θ that we vary between our benchmark calibrations with and without a government guarantee.

6.2 Economy with a Government Guarantee

In our first analysis, we ask whether we can match average prices on deep OTM puts and calls ($\Delta = 20$, TTM=365) on the financial sector index, the basket of financial stocks, and their spread in both the pre-crisis (state 1 in the model) and the crisis period (state 2). Simultaneously, we are interested in matching the correlation between return pairs and the volatility of index and individual returns in both states. These comprise 12 distinct moments. Our benchmark calibration for the

[19] Using the holdings from a different day has only minor quantitative effects on our results. This measure would only be half as large (0.11) if all 79 firms had equal size.

financial sector sets

$$\Theta^F = (\sigma_d, \xi_d, \underline{J}, \theta_r, \delta_r, \delta_d) = (0.15, 0, 0.921, 0.815, 0.55, 0.516).$$

Because the disaster probability is modest in state 1, Gaussian risk is what mostly drives the standard deviation of the index and the correlation among stocks in the pre-crisis period. The choice $\xi_d = 0$ implies that all the unpriced Gaussian dividend growth risk is idiosyncratic. This creates relatively more idiosyncratic risk, increasing the basket-index spread for both calls and puts in both states 1 and 2. It also allows us to lower the pairwise return correlation (by increasing σ_d) without causing much of an increase in the volatility of the index return. The choice $\sigma_d = .15$ allows us to match the 46% pairwise correlation between stock returns in the pre-crisis period. It generates financial index return volatility of 19%, which is reasonably close to the 12% volatility observed in the pre-crisis period.

We choose a high value for the aggregate tail risk parameter, $\theta_r = .815$, as well as a high dispersion, $\delta_r = .55$. This means that, absent bailout options, the financial sector would suffer a return drop of 81.5% in logs or 55.7% in levels, with a wide confidence interval around it. However, the bailout option $\underline{J}$ substantially limits the losses for the index. The mean loss θ_a, which takes into account the bailout, is 46.5% in logs or 37.2% in levels. At the same time, there is substantial idiosyncratic tail risk, $\delta_d = .516$, meaning that some firms fare much better than others in a financial disaster. Importantly, the bailout only applies to aggregate and not idiosyncratic tail risk. Our parameters are such that there is enough residual aggregate tail risk (after the bailout) to make all options expensive enough, and enough idiosyncratic tail risk to make individual options more expensive than index options. However, there cannot be too much idiosyncratic tail risk or else the pairwise correlation of stock returns would fall from state 1 to state 2, counter-factually implying very low correlation during a crisis. We return to this point in the next subsection.

As Panel B of Table V shows, our model is able to quantitatively account for observed option prices. It matches basket and index put prices in the crisis (state 2) perfectly. It also reproduces the correct level of put prices in the pre-crisis period (state 1), but it understates the put spread in state 1. The model is able to account for a large run-up in the put spread between the pre-crisis period and the crisis period. In the model, this is caused by a four-fold increase in the probability of a financial disaster. Similarly, the model generates the right prices for deep OTM call options. In particular, it captures the feature of the data that the call spread decreases from the pre-crisis to the crisis period. The model slightly overstates the call spreads. The option-implied volatility from the put index increases from 31.2% pre-crisis to 46.7% in the crisis inside the model. The latter number is only slightly above the model's realized index volatility in a disaster of 46.4%. The difference between option-implied and realized volatility shrinks substantially during the crisis: from 12% to 0.3%. In the data, the pattern is the same with implied volatility 9.8% above realized volatility pre-crisis, with this difference falling to 4.7% in the crisis. Panel B of Table VI shows that the model also generates an increase in the volatility of index returns, thanks to the large amount of aggregate tail risk. Finally, the model generates a substantial increase in the pairwise correlation of returns from pre-crisis to crisis. While it still understates the rise in the data, the increase is important and goes hand in hand with the bailout option. Intuitively, in state 1 the correlation mostly reflects Gaussian risk and the Gaussian correlation is low because all ϵ shocks are idiosyncratic. Because of the substantial amount of aggregate tail risk (relative to the idiosyncratic tail risk), the correlation between returns in the disaster state is higher (40% versus 16% in the non-disaster state). Since state 2 gives the disaster state more weight, the correlation rises from state 1 to 2. Absent a bailout, this amount of aggregate tail risk would lead to index option prices that are far too high compared to the data.

The large amount of idiosyncratic Gaussian and tail risk deliver individual stock returns that are volatile: 27% in the pre-crisis and 44.5% in the crisis. Conditional on a disaster, individual stock return volatility is 69.5%, not unlike the observed 72.9% realized volatility of individual financial firms during the crisis period. Implied volatility from the put basket is 61.3% during the crisis in the model, substantially below realized volatility of 69.5%. The same is true in the data, where implied volatility is 59.5%, below the realized volatility of 72.9%.

Finally, we find that the model generates the same implied volatility skew patterns for the basket-index spread as in the data. Pre-crisis, the implied volatility of the basket of options minus that of the index option is low and stable across moneyness. During the crisis, the basket-index skew shifts up and becomes much higher for $\Delta = 20$ options than for $\Delta = 50$ options.

6.3 Economy without a Bailout Guarantee

Having shown that we can match the option prices of interest in the presence of a bailout guarantee, we now show that the bailout guarantee is essential. To that end, we set $\underline{J} = +\infty$, and search over the remaining parameters of Θ to best match the 12 moments of interest. We find the best match at the following parameter values:

$$\Theta^{NB} = (\sigma_d, \xi_d, \underline{J}, \theta_r, \delta_r, \delta_d) = (0.15, .628, +\infty, 0.2825, 0.25, 0.65).$$

This calibration features a higher level of idiosyncratic tail risk and a much lower level of aggregate tail risk. The aggregate dividend falls 25% during a disaster, with substantially less dispersion around it. It also has a lower level of Gaussian tail risk because 2/3 of the ϵ shocks are now common across firms.

As Panel C of Table V shows, the model without a bailout guarantee matches put option prices in the crisis equally well. It also does a reasonably good job matching put prices in the pre-crisis period, but understating the put spread just like the model with bailouts. The match for call prices is worse than for the model with bailouts. In particular, this model shows a negative call spread in the pre-crisis which rises during the crisis. The opposite is true in the data. The implied volatility from basket calls and puts is about the same, while it is much lower for calls than for puts in the data. The latter again reflects the high degree of idiosyncratic tail risk in this calibration.

The main problem with this calibration, however, is that the correlation between stock returns goes *down* in the crisis, as can be seen in Panel C of Table VI. The reason is that correlations between stocks are very low during disasters in this model. In order to generate high spreads with no bailout, idiosyncratic tail risk must be set excessively high while aggregate tail risk is low. To match the pre-crisis correlation, the model must make most of the Gaussian risk systematic. This decline in correlation is a highly counter-factual and undesirable feature of the model without bailouts. Another counter-factual consequence of this is that idiosyncratic tail risk is so high that the price-dividend ratio of individual stocks blows up (it is 225,602 in levels while the one for the index is a reasonable 19).

6.4 Economy without Disaster Risk

Not only are we not able to explain the data in a model with financial disasters without government guarantees, we are also unable to account for the data in a model without disasters. To make this point, we study a standard Black-Scholes model with only Gaussian risk. To give this model a chance of explaining the data, we increase Gaussian consumption growth volatility to $\sigma_c(1) = 0.01$ pre-crisis and $\sigma_c(2) = 0.05$ during the crisis. We allow for the Gaussian risk to vary across two Markov states and set parameters $\sigma_d(1) = 0.133$, $\sigma_d(2) = 0.698$, $\xi_d(1) = .705$, $\xi_d(2) = 0.315$ so as to match the observed individual and index return volatility in the financial sector exactly. Matching the high individual return volatility of 72.9% in the crisis requires a large amount of idiosyncratic risk in state 2. Matching the index volatility of 43.8% during the crisis, requires assuming that 31.5% of Gaussian dividends shocks are common. Because the index volatility is relatively high compared to individual volatility, we need to choose a much higher fraction of common shocks in the pre-crisis period. This parameter configuration has the consequence of a very high 84% stock return correlation pre-crisis, which falls to 37% during the crisis. Again, this pattern is highly counter-factual. This calibration generates basket and index put prices that are essentially zero pre-crisis. During the crisis, it generates basket prices that are too high and index prices that are too low, so that the put spread is 7.8 in the model compared to 3.8 in the data. Call spreads go up in the model, but down in the data. We conclude that a Gaussian risk model cannot account for the patterns observed in the data and suffers from the same correlation problem as the disaster model without bailout guarantees.

6.5 Non-Financial Sectors

Next, we ask whether the model can explain the options prices and return moments for the non-financial sectors. We documented a smaller increase in put spreads between the pre-crisis and crisis averages, as repeated in the top panel of Table VII. Table VIII also shows a much smaller increase in the volatility of individual stock and index returns for non-financials than for financials. Volatilities are higher in the pre-crisis than for financials, but substantially lower during the crisis. Also, return correlations are lower, but increase to the same high level as for financials, implying a stronger overall increase. Matching these return facts necessitates a recalibration of the dividend growth parameters for the non-financial sector. All other parameters stay at their benchmark values. We choose

$$\Theta^{NF} = (\sigma_d, \xi_d, \underline{J}, \theta_r, \delta_r, \delta_d) = (0.17, 0.14, \infty, 0.219, 0.15, 0.23).$$

This calibration features no bailout option, substantially less idiosyncratic and aggregate tail risk, and slightly more unpriced Gaussian risk, a larger fraction of which is aggregate. This allows us to match the return volatility and correlation moments well, as shown in Panel B of Table VIII. The option prices in Panel B of Table VII also provide a good match to the put prices in the crisis. They generate the 1.6 cents put spread of the data. They also generate a large increase in the put spread from pre-crisis to crisis. The model also captures the decline in the call spread that we found in the data, but overstates OTM call price levels and spreads somewhat. These results suggests that, to a first-order approximation, it is appropriate to think of the bailout guarantee as being confined to the financial sector. However, a modest bailout guarantee may be needed to explain the maximum (as opposed to the average) put spread in the non-financial sector.

We argued that the presence of a bailout option should more strongly affect put than call spreads, crisis than pre-crisis period, and financial than non-financial firms. To quantify this prediction, we construct a triple difference of basket-index spreads: we subtract from the change over time in put spreads the change over time in call spreads. We then subtract that number for the financial sector from that for the non-financial sector. In the data, the triple difference is 2.44

cents per dollar insured. The calibrated model generates a very similar positive triple difference of 2.32.

6.6 Cost of Capital and Systemic Risk Measurement

We now use the model's parameters to gauge the effect of the bailout option on the cost of capital of financial firms and to compute a measure of the total value of the subsidy implied by the collective bailout guarantee.

The benchmark model's equity risk premium for the financial sector index is 4.7% per year in the pre-crisis and rises to 14.0% during the crisis. The bailout guarantee plays an important role in keeping the equity risk premium down. Without it, and holding all other parameters constant, the equity risk premium would be exactly twice as large. We conclude that option prices tell us that the bailout option substantially reduces the cost of capital for systemically risky financial firms. Similarly, we find that the price-dividend ratio in the model with bailout guarantees is 49.5% lower pre-crisis (in state 1) and 61% lower in the crisis state (state 2) than it would be absent guarantee. This implies that the bailout guarantee accounts for fully half of the value of the financial sector when calibrated to our sample.

Our model also enables us to measure systematic risk in the presence of a bailout guarantee. In particular, our calibration of the financial sector model with bailout guarantees delivers the aggregate amount of tail risk is that the financial sector takes on. Absent guarantees, the average financial firm would suffer a return fall of 55.7% in a financial disaster, compared to 37.2% with guarantees. The guarantee also affects the higher-order moments of the recovery distribution. The high and variable aggregate tail risk would presumably incur much higher (systemic) regulatory capital charges if detected and measured properly. The structural model allows us to do so.

6.7 Robustness

In section C of the separate appendix we consider several refinements of our benchmark model. First, we consider a calibration of the model that better matches the correlation increase during the crisis at the cost of a slightly worse fit of option prices. Second, we study a version of our economy that simultaneously matches put options of different moneyness. The basic implications from our benchmark economy carry over to this richer economy. Third, we consider a 3-state model that delivers larger increases in the basket-index spread by adding a third state with a much higher disaster probability.

So far, we have abstracted from bank heterogeneity. In section C.4, we extend the model to allow for banks of different sizes. Our model can account for the heterogeneity in option price and return features of each group of banks. We find that the cost of capital for large banks would increase by 12% points, 1.5 times the 9% point increase for the small banks. This suggests that large banks' options were "cheap" because they disproportionately enjoyed the government guarantee.

7 Alternative Explanations

We consider three alternative explanations to collective bailout options: mispricing and short sale restrictions, liquidity, and time-varying correlation risk premia. We conclude that none is consistent with the patterns in the data.

7.1 Mispricing and short-sale restrictions

Recent research has documented violations of the law of one price in several segments of financial markets during the crisis. In currency markets, violations of covered interest rate parity have been documented (see Garleanu and Pedersen, 2009). In government bond markets, there was mispricing between TIPS, nominal Treasuries and inflation swaps (see Fleckenstein, Longstaff, and Lustig, 2010). Finally, in corporate bond markets, large arbitrage opportunities opened up between CDS spreads and the CDX index and between corporate bond yields and CDS (see Mitchell and Pulvino, 2009). 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 does not require substantial capital, unlike some of these other trades (CDS basis trade, TIPS/Treasury trade). Hence, instances of mispricing in the options basket-index spread due to capital shortages are less likely to persist (see 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 counter-party risk. The state of the world in which the entire financial sector, or the whole economy, is at risk is the state of the world in which OTM index put options pay off. However, these are exchange traded options and hence are cleared through a clearing house; no clearing house has ever failed. All options transactions on the CBOE are cleared by the Options Clearing Corporation. This is the first clearinghouse to receive Standard & Poor's highest credit rating. Hence, these options are very unlikely to be affected by counterparty default risk.

Finally, our analysis of implied volatility on index options has established that these index options are cheap during the crisis even when comparing implied and realized volatility. This comparison does not rely on individual option prices, which may be more subject to mispricing.

A related alternative explanation involves 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 until October 8, 2008 which affected 800 financial stocks. From July 21, 2008 onwards, 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 where exempted from both SEC rules so that they could continue to provide liquidity and hedge their positions during the ban. Both the short window of the ban compared to the period over which the put spread increased (recall it peaks first on October 13 after the ban is lifted and again in March 2009) and the exemption for market makers make the short sale ban an unlikely explanation for our findings.

7.2 Liquidity

Another potential alternative explanation of our findings is that individual put options are more liquid than index put options, and that their relative liquidity rose during the financial crisis. The same explanation must also apply to call options. We now argue that these liquidity facts are an unlikely explanation for our findings, often pointing in the opposite direction.

Table IX reports summary statistics for the liquidity of *put* options on the S&P 500 index, sector indices (a value-weighted average across all 9 sectors), the financial sector index, all individual stock options (a value-weighted average), and individual financial stock options. The table reports daily averages of the bid-ask spread in dollars, the bid-ask spread in percentage of the midpoint price, trading volume, and open interest. The columns cover the full range of moneyness, from deep OTM ($\Delta < 20$) to deep ITM ($\Delta > 80$), while the rows report a range of option maturities. We separately report averages for the pre-crisis and crisis periods. It is worth pointing out that a substantial fraction of trade in index options takes place in over-the-counter markets, which are outside our database. Hence, these bid-ask and volume numbers overstate the degree of illiquidity. However, absent arbitrage opportunities across trading locations, the option prices in our database do reflect this additional liquidity.

Deep OTM put options with $\Delta < 20$ have large spreads, and volume is limited. OTM puts with Δ between 20 and 50 still have substantial option spreads. For the long-dated OTM puts (maturity in excess of 180 days), the average pre-crisis spread is 5.5% for the S&P 500, 12.8% for the sector options, 10.8% for the financial sector options, 6.8% for all individual stock options, and 7.0% for individual stock options in the financial sector. Financial sector index options appear, if anything, 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.

Interestingly, during the crisis, the liquidity of the options appears to increase. For long-dated OTM puts, the spreads decrease from 5.5% to 4.7% for S&P 500 options, from 12.8 to 7.8% for sector options, from 10.8% to 4.5% for financial sector options, from 6.8 to 5.5 % for all individual options, and from 7.0% to 5.8% for financial firms' options.[20] At the same time, volume and

[20]Absolute bid-ask spreads increase during the crisis but this is explained by the rise in put prices during the

open interest for long-dated OTM puts increased. For example, volume increased from 400 to 507 contracts for the S&P 500 index options, from 45 to 169 for the sector options, from 287 to 1049 for financial index options, and from 130 to 162 for individual stock options in the financial sector. During the crisis, trade in OTM financial sector put options invariably exceeds not only trade in the other sector OTM put options but also trade in the OTM S&P 500 options. The absolute increase in liquidity of financial sector index puts during the crisis and the relative increase versus individual put options suggests that index options should have become more expensive, not cheaper during the crisis.

Short-dated put options (with maturity less than 10 days) are more liquid than long-dated options; they experience a larger increase in trade during the crisis. We verified above that our results are robust across option maturities. When expressed in comparable units, the increase in the basket-index put spread seemed larger for short-dated maturities, if anything.

Table X reports the same liquidity statistics for calls. Calls and puts are similarly liquid yet display very different basket-index spread behavior. Finally, the increase in the basket-index spread during the crisis is also (and even more strongly) present in shorter-dated options, which are more liquid. All these facts suggest that illiquidity is an unlikely candidate.

7.3 Time-Varying Price of Correlation Risk

Index put options are typically considered expensive relative to individual options. Returns on index put options are large and negative: -90% per month for deep OTM put options (see Bondarenko, 2003). CAPM alphas are large and negative as well, and Sharpe ratios on put writing strategies are larger than those on the underlying index. However, this does not imply these options are mispriced (see Broadie, Chernov, and Johannes, 2009). Stochastic volatility models and models with jumps can explain many features of these returns.

Driessen et al. (2009) attribute the expensiveness of index options to a negative correlation risk premium. The value of an index option increases when correlations of the basket constituents increase. This is because an increase in correlation constitutes a deterioration in the investment

crisis. Absolute bid-ask spreads increase by less than the price.

opportunity set, and index options provide investors with a hedge against such increases. A related stylized fact is that the implied index volatility is always higher than the expected realized index volatility, but the implied volatilities for individual stocks are not significantly higher than their expected realized volatilities. These features arise from models with (i) a zero risk price for idiosyncratic variance risk and (ii) a negative risk price for correlation risk.

We showed that the patterns for financial sector put options during the crisis were exactly the opposite. Implied volatility is often lower than the realized volatility for the index but not for the individual stocks during the crisis, and the index put option decreases in price relative to the individual options despite an increase in return correlations. These patterns for puts could in principle be consistent with a decrease in the price of correlation risk (in absolute value) over time. But, if anything, one would expect the price of correlation risk to increase in absolute value during the crisis. Furthermore, such a decreased price of correlation risk would have counter-factual implications for call spreads, which would be predicted to increase as well. The data instead show a decline in call spreads during the crisis.

8 Conclusion

Our paper uncovers new evidence from option prices showing that the government absorbs aggregate tail risk. By providing guarantees for the financial sector, the government effectively bends down the implied volatility skew for index put options on the financial sector. We propose a structural model that can disentangle true exposure to aggregate tail risk from exposure implied by market prices and thus accounts for distortions due to the implicit promise of bailouts. Our model identifies the magnitude of the collective bailout guarantee to the financial sector from the difference between the price of a basket of put options on individual financial firms and the price of a put option on the financial sector index. It ascribes the increase in the put spread to an increased probability of a financial disaster. During such periods, there is an increase in the relative amount of aggregate versus idiosyncratic tail risk, which helps to explain the increased return correlation between stocks. Put spreads can only rise because of a collective bailout guarantee which makes index options artificially cheap. Our model calibration suggests that the government's backstop massively reduced the cost-of-capital to the financial sector over our 2003-2009 sample. The substantial amount of aggregate tail risk the sector takes on would lead to a fifty percent reduction in its market value if the guarantee were taken away.

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Table I: Basket-Index Spreads on Out-of-the-Money Options

		Financials		Non-financials		F Minus NF			Financials		Non-financials		F Minus NF		
		Puts	Calls	Puts	Calls	Puts	Calls	P Minus C	Puts	Calls	Puts	Calls	Puts	Calls	P Minus C
		Panel I: Δ-Matched $TTM = 365$							Panel II: Strike Matched $TTM = 365$						
Full Sample	mean	1.693	0.238	1.106	0.208	0.588	0.030	0.558	2.936	0.990	2.686	2.019	0.250	-1.029	1.279
	std	1.891	0.157	0.686	0.094	1.435	0.100	1.506	2.516	0.100	1.076	0.246	1.693	0.194	1.846
	min	-0.133	-0.437	-0.122	-0.253	-1.899	-0.498	-1.732	1.019	0.632	1.265	1.663	-2.031	-1.943	-0.887
	max	12.458	0.487	4.128	0.359	9.070	0.440	9.568	15.872	1.273	7.579	2.754	10.168	-0.709	12.111
Pre-Crisis	mean	0.810	0.315	0.911	0.249	-0.098	0.067	-0.165	1.710	0.951	2.259	1.896	-0.549	-0.945	0.396
	std	0.197	0.056	0.442	0.052	0.335	0.052	0.326	0.345	0.070	0.587	0.128	0.329	0.085	0.269
	min	0.078	0.032	-0.033	0.101	-1.899	-0.225	-1.732	1.061	2.322	4.070	1.265	-2.031	0.942	1.943
	max	2.269	0.487	3.090	0.359	0.953	0.198	0.870	3.763	5.097	9.651	4.567	0.444	2.082	3.101
Crisis	mean	3.792	0.055	1.572	0.111	2.220	-0.057	2.277	5.851	1.082	3.702	2.313	2.149	-1.230	3.379
	std	2.393	0.166	0.904	0.100	1.705	0.130	1.791	3.006	0.101	1.274	0.206	2.076	0.230	2.253
	min	-0.133	-0.437	-0.122	-0.253	-0.538	-0.498	-0.740	1.019	0.632	1.776	1.867	-1.203	-1.943	-0.223
	max	12.458	0.370	4.128	0.285	9.070	0.440	9.568	15.872	1.273	7.579	2.754	10.168	-0.709	12.111
		Panel III: Δ-Matched, $TTM = 30$							Panel IV: Strike Matched, $TTM = 30$						
Full Sample	mean	0.302	0.139	0.158	0.116	0.145	0.023	0.122	0.683	0.430	0.576	0.559	0.107	-0.129	0.236
	std	0.334	0.064	0.136	0.054	0.274	0.085	0.302	0.612	0.156	0.251	0.156	0.414	0.076	0.405
	min	-0.150	-0.312	-0.831	-0.202	-0.415	-0.433	-0.424	0.170	-0.010	-0.529	0.241	-0.385	-0.613	-0.207
	max	2.458	0.272	0.651	0.240	1.865	0.324	2.031	3.977	1.081	1.976	1.308	2.663	0.204	2.777
Pre-Crisis	mean	0.170	0.155	0.129	0.105	0.042	0.051	-0.009	0.400	0.352	0.476	0.483	-0.076	-0.131	0.055
	std	0.063	0.054	0.110	0.052	0.119	0.072	0.095	0.074	0.047	0.137	0.070	0.118	0.071	0.090
	min	-0.072	-0.227	-0.831	-0.103	-0.316	-0.347	-0.424	0.170	0.535	0.948	-0.529	-0.385	0.236	0.636
	max	0.376	0.270	0.511	0.240	0.996	0.324	0.869	0.757	1.710	2.257	0.947	0.860	0.954	1.384
Crisis Sample	mean	0.617	0.100	0.228	0.144	0.389	-0.044	0.434	1.360	0.618	0.814	0.743	0.546	-0.126	0.671
	std	0.476	0.071	0.163	0.048	0.367	0.077	0.386	0.782	0.165	0.297	0.151	0.527	0.085	0.518
	min	-0.150	-0.312	-0.139	-0.202	-0.415	-0.433	-0.185	0.245	0.159	0.359	0.361	-0.181	-0.613	-0.014
	max	2.458	0.272	0.651	0.238	1.865	0.253	2.031	3.977	1.081	1.976	1.308	2.663	0.204	2.777

This table reports summary statistics for the basket-index spread in the cost of insurance per dollar insured. Numbers reported are in cents per dollar of the strike price. The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. Δ is 20. In the top panel, Time to maturity is 365 days. In Panel I, we choose the index option with the same Δ as the individual options. In Panel II, we choose the index option with the same share-weighted strike price as the basket.

Table II: Basket-Index Spreads on Out-of-the-Money Options in Other Sectors

		Put Spread		
Sector		Full Sample	Pre-Crisis	Crisis
Financials	Mean	1.69	0.81	3.80
	Max	12.46	2.27	12.46
Consumer Disc.	Mean	2.27	1.84	3.28
	Max	9.02	4.67	9.02
Materials	Mean	1.69	1.18	2.91
	Max	7.70	2.95	7.70
Technology	Mean	1.95	1.68	2.59
	Max	6.68	4.13	6.68
Healthcare	Mean	1.40	1.09	2.13
	Max	5.95	3.78	5.95
Industrials	Mean	1.81	1.65	2.19
	Max	4.73	3.74	4.73
Consumer Staples	Mean	1.35	1.15	1.84
	Max	5.91	2.52	5.91
Utilities	Mean	0.63	0.53	0.86
	Max	4.10	2.56	4.10
Energy	Mean	0.95	0.89	1.07
	Max	3.47	3.41	3.47

This table reports the average basket-index put spread in the cost of insurance per dollar insured for the nine S&P 500 sector ETFs. Numbers reported are in cents per dollar of the strike price. The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. $|\Delta|$ is 20, time to maturity is 365 days and spreads are calculated using Δ-matched options. Sectors are listed in descending order by mean crisis spread.

Table III: Summary Stats for Spreads on Options sorted by Moneyness

		Financials		Non-financials		F Minus NF			Financials		Non-financials		F Minus NF		
		Puts	Calls	Puts	Calls	Puts	Calls	P Minus C	Puts	Calls	Puts	Calls	Puts	Calls	P Minus C
		Δ = 20							Δ = 30						
Full	mean	1.693	0.238	1.106	0.208	0.588	0.030	0.558	2.133	0.459	1.514	0.421	0.621	0.039	0.582
	std	1.891	0.157	0.686	0.094	1.435	0.100	1.506	2.030	0.289	0.761	0.155	1.507	0.201	1.646
	min	-0.133	-0.437	-0.122	-0.253	-1.899	-0.498	-1.732	0.227	-1.036	-0.023	-0.285	-2.214	-1.186	-1.839
	max	12.458	0.487	4.128	0.359	9.070	0.440	9.568	14.090	0.843	5.345	0.683	11.002	0.789	11.691
Pre-Crisis	mean	0.810	0.315	0.911	0.249	-0.098	0.067	-0.165	1.193	0.593	1.292	0.489	-0.096	0.104	-0.201
	std	0.197	0.056	0.442	0.052	0.335	0.052	0.326	0.293	0.105	0.480	0.084	0.338	0.106	0.290
	min	0.078	2.593	3.265	-0.033	-1.899	0.942	1.410	0.227	0.101	-0.023	0.269	-2.214	-0.442	-1.839
	max	2.269	5.462	8.090	3.090	0.953	2.082	2.201	2.454	0.843	3.762	0.683	1.483	0.342	1.308
Crisis	mean	3.792	0.055	1.572	0.111	2.220	-0.057	2.277	4.370	0.142	2.042	0.258	2.328	-0.116	2.444
	std	2.393	0.166	0.904	0.100	1.705	0.130	1.791	2.573	0.336	1.006	0.165	1.807	0.277	2.007
	min	-0.133	-0.437	-0.122	-0.253	-0.538	-0.498	-0.740	0.479	-1.036	0.307	-0.285	-0.520	-1.186	-0.577
	max	12.458	0.370	4.128	0.285	9.070	0.440	9.568	14.090	0.753	5.345	0.577	11.002	0.789	11.691
		Δ = 40							Δ = 50						
Full	mean	2.581	0.763	1.968	0.702	0.615	0.062	0.553	3.083	1.161	2.487	1.079	0.599	0.083	0.516
	std	2.085	0.452	0.789	0.229	1.558	0.350	1.794	2.131	0.649	0.836	0.344	1.619	0.546	1.969
	min	0.522	-1.743	0.029	-0.241	-2.825	-2.154	-2.213	0.486	-2.770	0.348	-0.322	-4.086	-3.579	-2.737
	max	14.287	1.406	5.450	1.303	9.231	0.927	11.385	15.589	2.178	6.021	2.254	9.959	1.300	13.513
Pre-Crisis	mean	1.620	0.957	1.740	0.791	-0.116	0.167	-0.283	2.114	1.403	2.262	1.184	-0.145	0.221	-0.365
	std	0.305	0.175	0.519	0.152	0.441	0.191	0.378	0.328	0.278	0.586	0.266	0.514	0.277	0.394
	min	0.522	0.093	0.029	0.367	-2.825	-0.908	-2.213	0.586	0.375	0.348	0.173	-4.086	-1.349	-2.737
	max	2.955	1.406	4.771	1.303	2.033	0.584	1.705	4.015	2.178	5.895	2.254	2.290	1.187	1.734
Crisis	mean	4.867	0.303	2.511	0.490	2.356	-0.188	2.544	5.387	0.586	3.019	0.830	2.368	-0.244	2.613
	std	2.655	0.563	1.022	0.243	1.855	0.489	2.215	2.748	0.877	1.069	0.380	1.946	0.820	2.546
	min	0.643	-1.743	0.325	-0.241	-0.734	-2.154	-0.469	0.486	-2.770	0.719	-0.322	-1.287	-3.579	-1.246
	max	14.287	1.294	5.450	0.984	9.231	0.927	11.385	15.589	2.084	6.021	1.594	9.959	1.300	13.513

This table reports summary statistics for the basket-index spread in the cost of insurance per dollar insured. Numbers reported are in cents per dollar insured. The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. We choose the index option with the same Δ as the individual options.

Table IV: Percentage Basket-Index Spreads on Options with Varying Moneyness

		Financials		Non-financials	
		Puts	Calls	Puts	Calls
		$\Delta = 20$			
Full Sample	mean	29.69%	18.41%	25.23%	13.70%
	std	9.38%	11.95%	7.45%	7.09%
	max	80.53%	51.73%	64.48%	27.34%
Pre-Crisis Sample	mean	26.67%	24.68%	26.04%	16.91%
	std	5.78%	6.80%	7.47%	4.94%
	max	43.71%	51.73%	64.48%	0.36%
Crisis Sample	mean	36.86%	3.47%	23.28%	6.05%
	std	12.04%	7.46%	7.02%	5.38%
	max	80.53%	20.97%	44.97%	16.81%
		$\Delta = 30$			
Full Sample	mean	28.22%	19.29%	24.16%	14.97%
	std	7.66%	12.03%	5.73%	6.80%
	max	68.84%	48.15%	54.68%	28.54%
Pre-Crisis Sample	mean	26.84%	25.47%	25.19%	18.18%
	std	6.19%	7.09%	5.50%	4.46%
	max	44.00%	48.15%	54.68%	0.68%
Crisis Sample	mean	31.50%	4.41%	21.67%	7.25%
	std	9.61%	7.62%	5.48%	4.98%
	max	68.84%	22.08%	37.75%	18.57%
		$\Delta = 40$			
Full Sample	mean	27.99%	19.72%	24.27%	15.35%
	std	7.17%	11.91%	5.23%	6.46%
	max	57.82%	51.69%	50.85%	29.28%
Pre-Crisis Sample	mean	27.87%	25.69%	25.67%	18.29%
	std	6.78%	7.46%	4.96%	4.54%
	max	47.14%	51.69%	50.85%	1.30%
Crisis Sample	mean	28.22%	5.39%	20.89%	8.29%
	std	8.04%	7.57%	4.23%	4.68%
	max	57.82%	23.14%	33.41%	19.69%
		$\Delta = 50$			
Full Sample	mean	28.17%	19.49%	24.73%	15.52%
	std	7.26%	11.35%	5.42%	6.41%
	max	51.71%	55.53%	51.46%	29.75%
Pre-Crisis Sample	mean	29.02%	24.93%	26.49%	18.21%
	std	7.13%	7.62%	5.03%	4.92%
	max	47.47%	55.53%	51.46%	2.24%
Crisis Sample	mean	26.11%	6.43%	20.48%	9.07%
	std	7.19%	7.53%	3.69%	4.73%
	max	51.71%	24.35%	32.70%	21.26%

This table reports summary statistics for the basket-index spread. Numbers reported are in percent of the cost of the index put. The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. Δ is 20. We choose the index option with the same Δ as the individual options.

Table V: Option Prices in Benchmark Economy in Financial Sector

The table reports option prices and implied volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the financial sector index. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.516$, $\underline{J} = 0.921$, $\theta_r = 0.815$, and $\delta_r = 0.55$. Panel C sets $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.65$, $\underline{J} = +\infty$, $\theta_r = 0.2825$, and $\delta_r = 0.25$.

	Puts			Calls		
	Basket	Index	Spread	Basket	Index	Spread
			Panel I: Data			
			Option Prices			
pre-crisis	4.0	3.2	0.8	1.6	1.3	0.3
crisis	13.7	9.9	3.8	2.4	2.3	0.1
			Implied Vol			
pre-crisis	25.9	21.7	4.2	19.8	14.9	4.9
crisis	59.5	48.5	11.0	42.8	37.8	5.0
			Panel II: Model with Bailout			
			Option Prices			
pre-crisis	4.3	4.1	0.3	1.5	1.2	0.4
crisis	13.7	9.9	3.8	2.5	2.3	0.2
			Implied Vol			
pre-crisis	34.1	31.2	2.9	17.4	11.0	6.5
crisis	61.3	46.7	14.6	35.0	24.1	10.9
			Panel III: Model without Bailout			
			Option Prices			
pre-crisis	3.8	3.4	0.4	1.5	1.6	-0.1
crisis	13.7	9.9	3.8	2.6	2.3	0.3
			Implied Vol			
pre-crisis	32.2	29.2	3.0	17.7	18.2	-0.5
crisis	62.9	48.6	14.3	61.0	27.7	33.3

Table VI: Returns in Benchmark Economy in Financial Sector

The table reports realized volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the financial sector index. The crisis numbers for the model represent the unconditional moment in state 2, taking disasters into account probabilistically. The number *in italic* for the model report the moments in state 2 of the model *conditional* on a disaster realization. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.516$, $\underline{J} = 0.921$, $\theta_r = 0.815$, and $\delta_r = 0.55$. Panel C sets $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.65$, $\underline{J} = +\infty$, $\theta_r = 0.2825$, and $\delta_r = 0.25$.

	Index	**Individual Stocks**	
	Volatility	Volatility	Correlations
		Panel I: Data	
pre-crisis	11.9	18.1	45.8
crisis	43.8	72.9	57.6
		Panel II: Model with Bailout	
pre-crisis	19.2	26.7	42.3
crisis	31.9	44.5	51.1
	46.4	*69.5*	*40.7*
		Panel III: Model without Bailout	
pre-crisis	18.7	26.0	43.8
crisis	28.7	44.4	35.8
	42.8	*76.7*	*26.7*

Table VII: Option Prices in Benchmark Economy in Non-Financial Sector

The table reports option prices and implied volatility for the non-financial sector index, for its constituents, and pairwise correlations between the stocks in the financial sector index. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.17$, $\xi_d(1) = \xi_d(2) = 0.14$, $\delta_d = 0.23$, $\underline{J} = +\infty$, $\theta_r = 0.219$, and $\delta_r = 0.15$.

	Puts			Calls		
	Basket	Index	Spread	Basket	Index	Spread
			Panel I: Data			
			Option Prices			
pre-crisis	4.3	3.4	0.9	1.8	1.5	0.3
crisis	7.9	6.3	1.6	2.2	2.0	0.1
			Implied Vol			
pre-crisis	28.6	21.7	6.9	23.2	15.9	7.3
crisis	41.7	34.2	7.5	32.1	24.3	7.8
			Panel II: Model without Bailout			
			Option Prices			
pre-crisis	2.8	2.3	0.5	1.5	0.9	0.6
crisis	7.9	6.3	1.6	2.0	1.6	0.4
			Implied Vol			
pre-crisis	27.1	22.4	4.7	17.0	8.4	8.6
crisis	42.6	35.6	7.0	25.1	20.0	5.1

Table VIII: Returns in Model and Data in Non-financial Sector

The table reports realized volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the non-financial sector index. The crisis numbers for the model represent the unconditional moment in state 2, taking disasters into account probabilistically. The number *in italic* for the model report the moments in state 2 of the model *conditional* on a disaster realization. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.17$, $\xi_d(1) = \xi_d(2) = 0.14$, $\delta_d = 0.23$, $\underline{J} = +\infty$, $\theta_r = 0.219$, and $\delta_r = 0.15$.

	Index	**Individual Stocks**	
	Volatility	Volatility	Correlations
		Panel I: Data	
pre-crisis	12.2	21.5	33.7
crisis	25.1	35.1	56.8
		Panel II: Model without Bailout	
pre-crisis	12.7	20.7	33.2
crisis	19.9	27.7	48.2
	28.7	*39.5*	*50.1*

Table IX: Liquidity in Puts

	$0 \leq \Delta < 20$				$20 \leq \Delta < 50$				$50 \leq \Delta < 80$				$80 \leq \Delta < 100$			
	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.
Pre-Crisis Sample									**10 Days < $TTM \leq$ 90 Days**							
S&P 500	0.450	80.5%	1072	15783	1.295	9.4%	2219	16594	1.821	5.8%	693	6807	1.959	3.7%	93	3138
All Sector SPDRs	0.133	150.5%	80	3205	0.141	35.0%	867	7606	0.167	13.7%	269	3221	0.239	7.9%	26	339
Financial SPDR	0.096	142.3%	187	10494	0.109	30.9%	1791	19708	0.125	12.4%	502	7907	0.182	7.0%	44	689
Indiv. Stocks	0.088	106.3%	169	5447	0.106	13.2%	836	9225	0.152	6.2%	473	5990	0.230	3.1%	76	1550
Fin. Indiv. Stocks	0.095	103.5%	142	4534	0.116	13.4%	691	7667	0.169	6.4%	380	4888	0.254	3.3%	65	1288
									90 Days < $TTM \leq$ 180 Days							
S&P 500	0.701	56.3%	373	18107	1.719	6.9%	1242	22052	1.982	3.4%	198	5962	2.076	1.5%	14	1949
All Sector SPDRs	0.141	96.0%	21	1132	0.156	19.0%	163	3057	0.198	8.7%	40	1258	0.273	6.3%	3	118
Financial SPDR	0.103	71.0%	103	4307	0.119	16.8%	452	13713	0.142	7.6%	96	3891	0.182	4.9%	16	347
Indiv. Stocks	0.094	72.4%	66	4326	0.133	8.1%	278	7760	0.196	4.3%	123	4622	0.242	2.3%	21	1138
Fin. Indiv. Stocks	0.103	68.4%	56	3445	0.147	8.3%	229	6509	0.216	4.4%	103	3565	0.271	2.5%	18	807
									180 Days < $TTM \leq$ 365 Days							
S&P 500	1.067	33.7%	237	12015	2.093	5.5%	400	10895	2.185	2.6%	52	2837	2.174	1.1%	4	1359
All Sector SPDRs	0.130	60.6%	9	857	0.156	12.8%	45	1290	0.203	6.8%	10	593	0.273	4.7%	2	129
Financial SPDR	0.095	47.5%	24	2448	0.105	10.8%	287	7823	0.139	5.6%	53	3313	0.188	4.0%	4	128
Indiv. Stocks	0.103	55.3%	52	4432	0.156	6.8%	170	6880	0.224	3.8%	65	4040	0.255	2.1%	15	1208
Fin. Indiv. Stocks	0.112	49.8%	48	3782	0.174	7.0%	130	5582	0.247	3.9%	50	2972	0.278	2.2%	11	756
Crisis Sample									**10 Days < $TTM \leq$ 90 Days**							
S&P 500	1.120	61.7%	1369	14797	2.663	9.4%	2652	18992	2.974	4.5%	871	14305	3.033	2.4%	120	9284
All Sector SPDRs	0.087	59.4%	667	8801	0.130	11.8%	2849	20540	0.226	6.9%	963	12846	0.388	4.8%	72	3724
Financial SPDR	0.042	24.7%	4422	52042	0.054	6.5%	12983	88367	0.107	4.4%	4336	56684	0.206	3.7%	376	19916
Indiv. Stocks	0.108	55.5%	344	5590	0.153	7.9%	1170	9400	0.244	4.5%	529	6857	0.481	2.9%	87	2404
Fin. Indiv. Stocks	0.126	56.2%	296	4390	0.181	8.1%	1041	8047	0.288	4.6%	452	5741	0.516	3.0%	83	2435
									90 Days < $TTM \leq$ 180 Days							
S&P 500	1.723	35.2%	568	16641	3.003	6.2%	1147	18511	3.179	2.8%	212	12697	3.255	1.3%	25	7625
All Sector SPDRs	0.112	31.1%	209	4218	0.184	8.1%	527	8681	0.286	4.9%	162	5310	0.407	3.6%	17	1598
Financial SPDR	0.055	18.7%	1421	24285	0.079	5.3%	3012	49466	0.159	4.0%	1008	28769	0.227	3.0%	129	8338
Indiv. Stocks	0.133	38.2%	119	4640	0.214	5.5%	339	7705	0.318	3.2%	115	4908	0.492	2.2%	15	1593
Fin. Indiv. Stocks	0.154	37.9%	106	3405	0.253	5.6%	301	6235	0.376	3.3%	94	4085	0.536	2.2%	16	1637
									180 Days < $TTM \leq$ 365 Days							
S&P 500	2.402	22.3%	272	12355	3.409	4.7%	507	13293	3.538	2.1%	60	7814	3.593	1.1%	8	5226
All Sector SPDRs	0.177	22.1%	57	1693	0.300	7.8%	169	3428	0.410	4.8%	50	3257	0.474	3.3%	44	1818
Financial SPDR	0.057	12.9%	238	7318	0.089	4.5%	1049	19391	0.170	3.5%	300	13661	0.219	2.4%	121	6042
Indiv. Stocks	0.186	30.4%	69	2713	0.294	5.5%	173	5372	0.423	3.1%	55	3653	0.623	2.2%	9	1269
Fin. Indiv. Stocks	0.208	30.6%	54	1984	0.338	5.8%	162	4654	0.474	3.3%	47	3529	0.630	2.3%	9	1459

The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. The stats reported for individual and sector options are value-weighted.

Table X: Liquidity in Calls

	$0 \leq \Delta < 20$				$20 \leq \Delta < 50$				$50 \leq \Delta < 80$				$80 \leq \Delta < 100$			
	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.	Spr. ($)	Spr. (%)	Vol.	O.I.
Pre-Crisis Sample	**10 Days < $TTM \leq$ 90 Days**															
S&P 500	0.405	96.9%	1002	11990	1.204	10.3%	1598	12885	1.836	5.3%	930	11351	2.006	1.9%	71	3476
All Sector SPDRs	0.123	169.3%	23	745	0.135	42.3%	262	2970	0.160	14.3%	187	2790	0.236	7.4%	16	931
Financial SPDR	0.081	177.4%	22	1497	0.107	38.2%	512	6477	0.129	13.4%	311	6428	0.183	6.7%	28	1995
Indiv. Stocks	0.077	140.7%	203	5916	0.100	14.6%	1430	14839	0.144	6.1%	928	11702	0.229	3.1%	186	3840
Fin. Indiv. Stocks	0.083	138.1%	179	4926	0.110	15.1%	1145	11640	0.160	6.2%	738	9123	0.252	3.3%	142	3189
	90 Days < $TTM \leq$ 180 Days															
S&P 500	0.592	85.7%	301	10160	1.662	8.2%	703	17315	1.983	3.0%	364	13038	2.049	1.1%	22	3148
All Sector SPDRs	0.134	122.8%	8	434	0.154	24.1%	59	1481	0.195	9.1%	50	1365	0.282	5.9%	4	306
Financial SPDR	0.085	94.5%	12	1012	0.120	22.2%	134	4566	0.148	8.1%	109	3734	0.214	5.0%	7	748
Indiv. Stocks	0.082	112.2%	77	4798	0.122	9.5%	512	11756	0.187	4.5%	262	8052	0.251	2.4%	34	2248
Fin. Indiv. Stocks	0.089	111.2%	60	3468	0.136	9.9%	395	8320	0.207	4.6%	187	5686	0.279	2.5%	26	1567
	180 Days < $TTM \leq$ 365 Days															
S&P 500	0.872	50.0%	113	6705	2.001	6.9%	249	10021	2.198	2.3%	106	7283	2.224	0.9%	11	1200
Sector SPDRs	0.121	89.4%	3	455	0.151	17.2%	23	1070	0.204	7.0%	19	825	0.270	4.8%	2	258
Financial SPDR	0.088	64.8%	7	493	0.108	15.1%	48	2362	0.139	5.8%	45	2548	0.198	3.7%	3	497
Indiv. Stocks	0.090	93.6%	51	5189	0.143	8.5%	259	9021	0.215	4.1%	147	6730	0.271	2.2%	23	2363
Fin. Indiv. Stocks	0.096	96.1%	40	3962	0.158	8.9%	207	6783	0.238	4.3%	109	5349	0.292	2.3%	16	1877
Crisis Sample	**10 Days < $TTM \leq$ 90 Days**															
S&P 500	0.705	118.6%	580	10797	2.497	11.4%	1857	16012	2.968	4.3%	1047	9846	3.047	1.8%	50	2157
All Sector SPDRs	0.080	103.7%	390	7908	0.121	14.1%	3386	19642	0.211	7.2%	1552	11705	0.350	4.6%	98	2581
Financial SPDR	0.037	47.7%	3007	52259	0.050	8.5%	17312	93957	0.097	4.8%	8020	56259	0.178	4.0%	628	19025
Indiv. Stocks	0.094	96.6%	341	6754	0.141	9.5%	1623	11596	0.230	4.8%	838	7407	0.446	3.1%	103	2423
Fin. Indiv. Stocks	0.110	93.6%	293	5739	0.169	10.0%	1362	9587	0.263	4.9%	754	6157	0.490	3.3%	104	1742
	90 Days < $TTM \leq$ 180 Days															
S&P 500	1.067	97.4%	183	10138	2.913	8.8%	637	12846	3.167	3.0%	326	4394	3.219	1.3%	13	912
All Sector SPDRs	0.099	81.2%	109	4741	0.168	10.8%	480	7791	0.278	5.6%	219	3878	0.394	3.6%	19	702
Financial SPDR	0.051	50.3%	749	25321	0.077	8.2%	2916	42929	0.139	4.4%	1193	18780	0.219	3.5%	107	3391
Indiv. Stocks	0.118	75.5%	100	5023	0.197	7.5%	460	9358	0.299	3.9%	216	5972	0.496	2.5%	25	1818
Fin. Indiv. Stocks	0.136	73.9%	93	4523	0.236	7.9%	375	7207	0.350	4.1%	181	4543	0.537	2.7%	19	1269
	180 Days < $TTM \leq$ 365 Days															
S&P 500	1.625	66.6%	62	8211	3.420	7.7%	237	8752	3.500	2.5%	126	4713	3.485	1.1%	5	510
All Sector SPDRs	0.151	63.6%	45	2964	0.280	11.6%	162	4348	0.411	5.8%	77	2034	0.507	3.8%	6	431
Financial SPDR	0.054	35.2%	154	8949	0.088	7.5%	836	18346	0.151	4.1%	480	11201	0.207	3.0%	18	1960
Indiv. Stocks	0.159	62.1%	57	4033	0.274	8.0%	210	5991	0.395	4.2%	118	3886	0.609	2.8%	14	891
Fin. Indiv. Stocks	0.170	63.9%	54	4381	0.311	8.6%	190	5345	0.451	4.5%	103	3124	0.630	3.1%	13	702

The full sample covers 1/2003-6/2009. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009. The stats reported for individual and sector options are value-weighted.

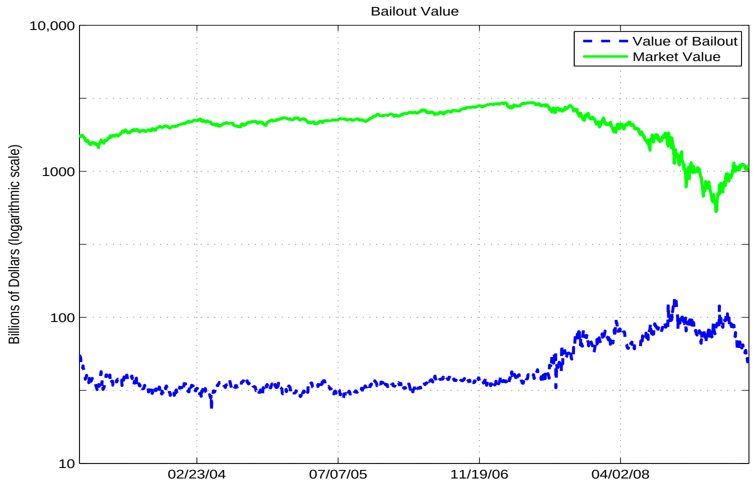

Figure 1: Dollar Value of the Equity Bailout Guarantee for the Financial Sector

The dashed (full) line shows the dollar value of the equity bailout guarantee inferred from the basket-index spreads for puts. Δ is 20. Time to maturity is 365 days. We choose the index options with the same Δ as the individual options.

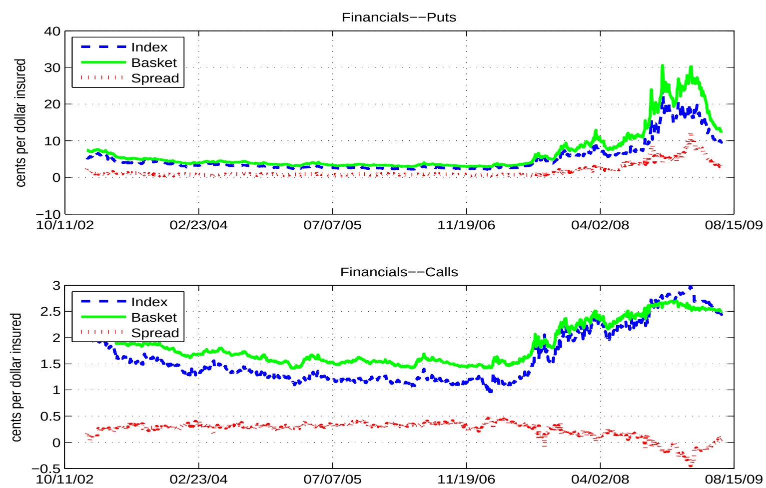

Figure 2: Cost Per Dollar Insured - Financial Sector

The dashed (full) line shows the cost per dollar insured for the index $Call^{index}_{cdi,f}$ (basket, $Call^{basket}_{cdi,f}$). The dotted line plots their difference. Δ is 20. Time to maturity is 365 days. We choose the index option with the same Δ as the individual options. The top panel looks at puts. The bottom looks at calls.

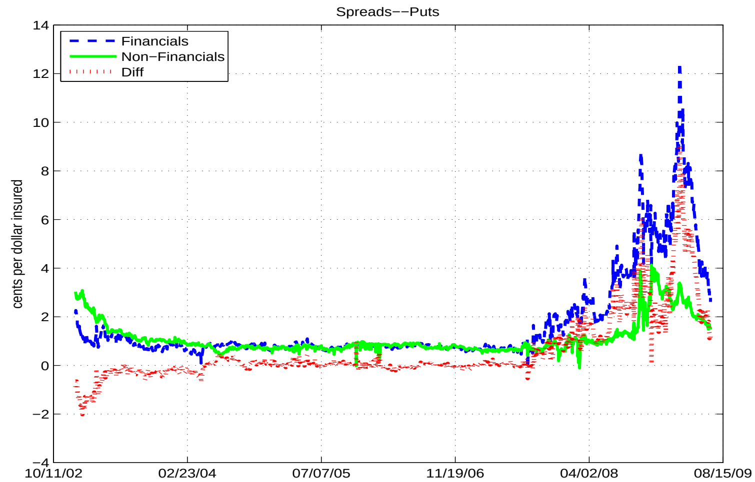

Figure 3: Basket-Index Spread in Cost Per Dollar Insured Inferred from Puts

The dashed (full) line shows the difference in the cost per dollar insured between the basket and the index: $Put^{basket}_{cdi,i} - Put^{index}_{cdi,i}$ for financials (non-financials). The dotted line plots their difference. Δ is 20. Time to maturity is 365 days. We choose the index option with the same Δ as the individual options.

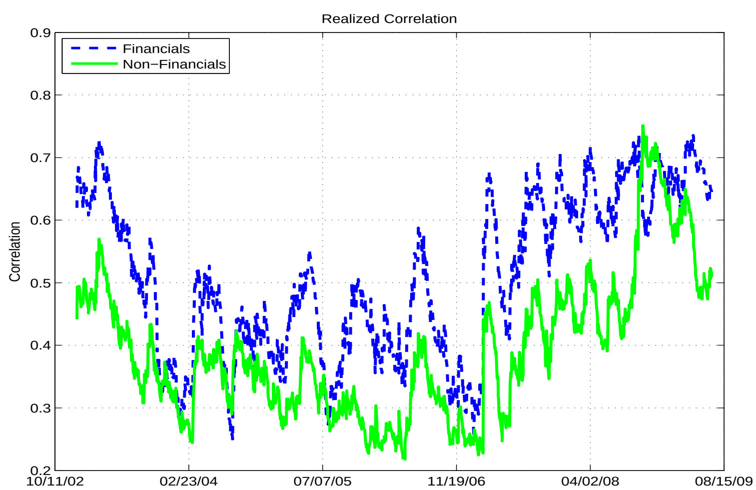

Figure 4: Realized Equity Return Correlations

The dashed (full) line shows the average pairwise correlations within the financial sector (non-financial sectors). Daily pairwise conditional correlations for stocks are estimated using the exponential smoother with smoothing parameter 0.95. Pairwise correlations within the financial sector are then averaged each day, weighted by the pairs' combined market equity. To address stocks' entry into and exit from the S&P 500 index during the sample period, a pair's correlation is only included in the average on a given day if both stocks were members of the index that day. To remain comparable to the average pairwise correlation among financial stocks, the non-financials average correlation reflects only correlations between pairs of stocks within the same sector, omitting cross-sector correlations from the average. The (within sector) pairwise correlations are then averaged across the eight non-financial sectors, according to their relative market capitalization.

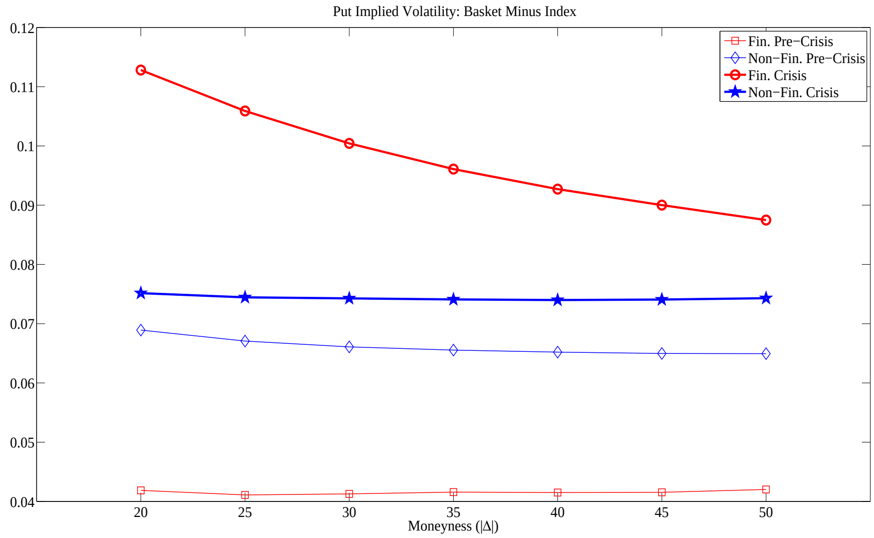

Figure 5: Implied Vol Skew Inferred from Puts

The figure plots the implied volatility difference (basket minus index) inferred from puts for financials against moneyness. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009.

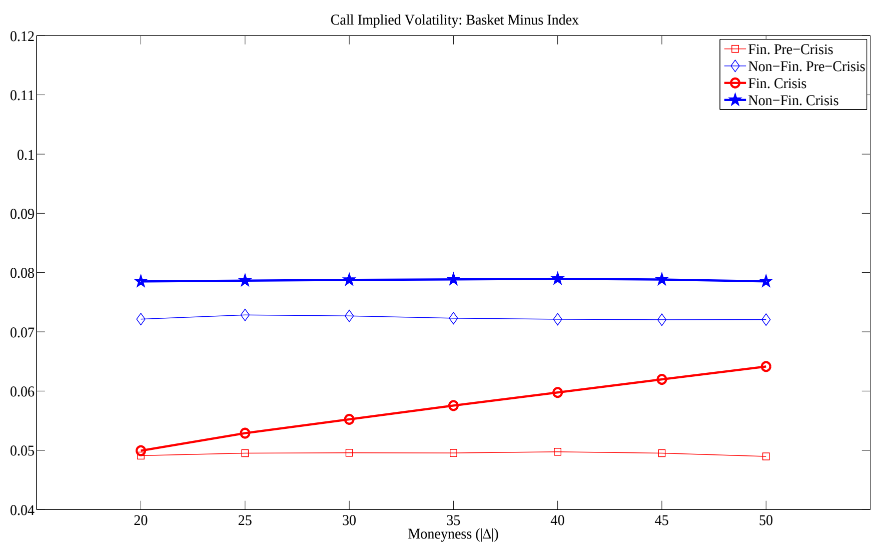

Figure 6: Implied Vol Skew Inferred from Calls

The figure plots the average implied volatility difference (basket minus index) inferred from calls for financials and non-financials against moneyness. The pre-crisis sample covers 1/2003-7/2007. The crisis sample covers 8/2007-6/2009.

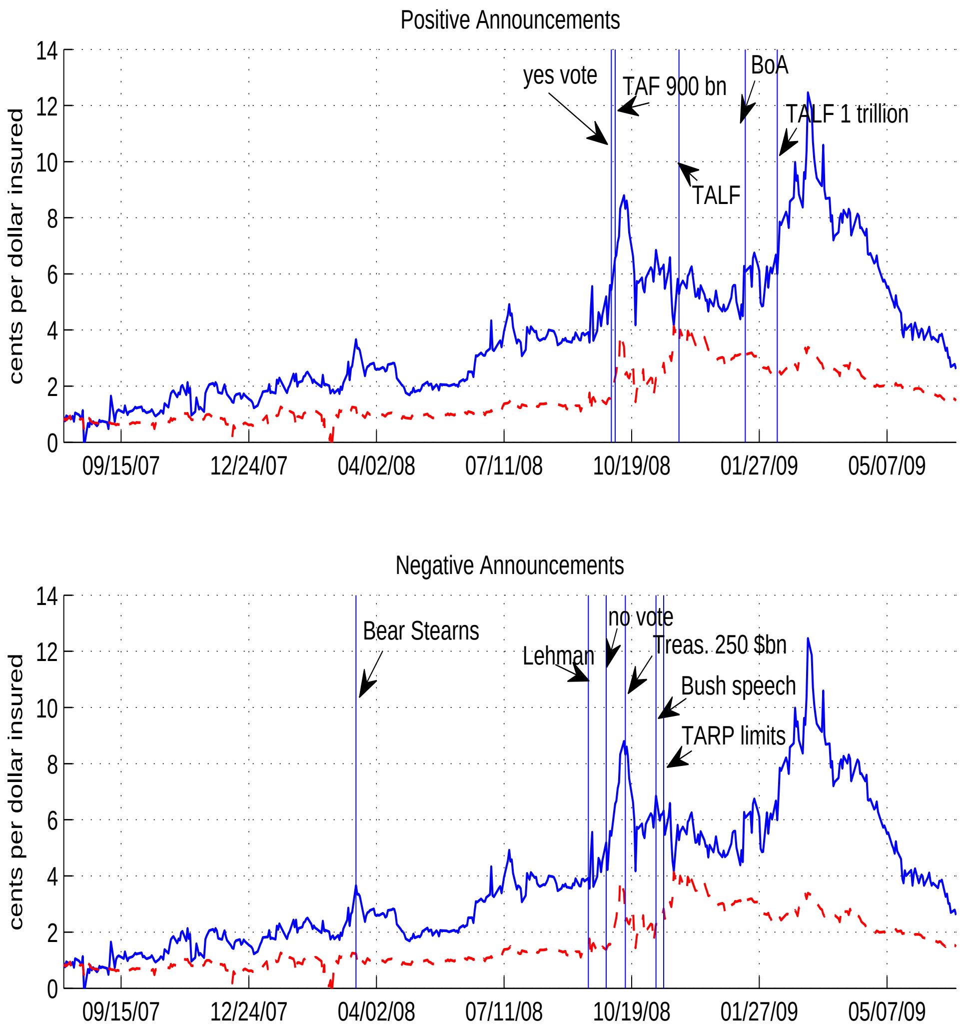

Figure 7: Timeline of The Financial Spread and Announcement Dates

The solid line shows the basket-index spread for the financials index $Put^{basket}_{cdi,f} - Put^{index}_{cdi,f}$. The dotted line shows the spread for non-financials. Δ is 20. Time to maturity is 365 days. The vertical lines are the announcement dates.

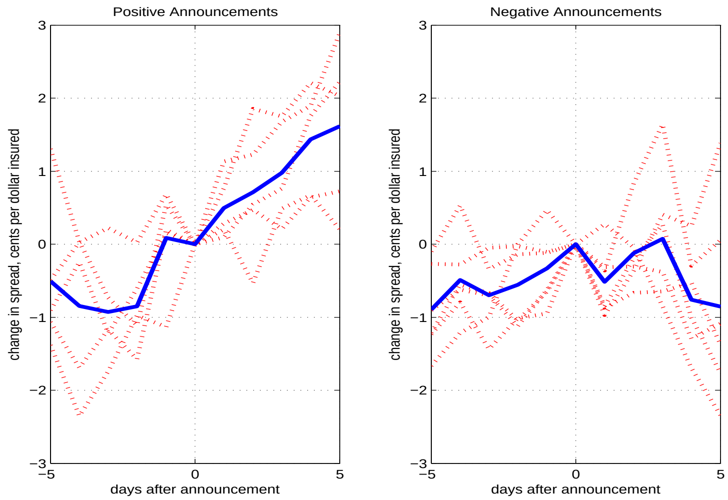

Figure 8: The Financial Spread around Announcement Dates

The solid line shows the average response of the basket-index spread for the financials index $Put^{basket}_{cdi,f} - Put^{index}_{cdi,f}$. The left panel looks at positive announcement dates. The right panel looks at negative announcement dates. Δ is 20. Time to maturity is 365 days.

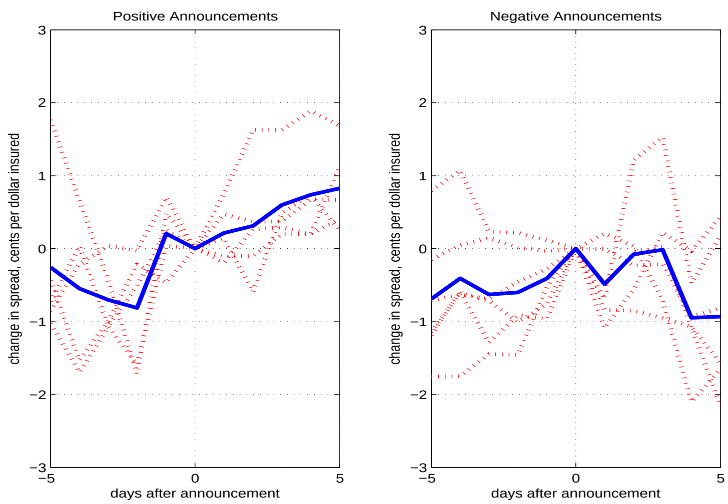

Figure 9: The Financial-minus-Non-financial Spread around Announcement Dates

The solid line shows the average response of the basket-index spread for the financials index minus the basket-index spread for the non-financials $Put^{basket}_{cdi,f} - Put^{index}_{cdi,f} - Put^{basket}_{cdi,nf} + Put^{index}_{cdi,nf}$. The left panel looks at positive announcement dates. The right panel looks at negative announcement dates. Δ is 20. Time to maturity is 365 days.

Separate Appendix–Not for Publication

A Data Appendix

The S&P 500 Index is an unmanaged index of 500 common stocks that is generally considered representative of the U.S. stock market. The Select Sector SPDR Trust consists of nine separate investment portfolios (each a Select Sector SPDR Fund or a Fund and collectively the Select Sector SPDR Funds or the Funds). Each Select Sector SPDR Fund is an index fund that invests in a particular sector or group of industries represented by a specified Select Sector Index. The companies included in each Select Sector Index are selected on the basis of general industry classification from a universe of companies defined by the Standard & Poor's 500 Composite Stock Index (S&P 500). The nine Select Sector Indexes (each a Select Sector Index) upon which the Funds are based together comprise all of the companies in the S&P 500. The investment objective of each Fund is to provide investment results that, before expenses, correspond generally to the price and yield performance of publicly traded equity securities of companies in a particular sector or group of industries, as represented by a specified market sector index. The financial sector's ticker is XLF. Table A reports the XLF holdings before and after the crisis.

B Model Appendix

B.1 Valuing the Consumption Claim

We start by valuing the consumption claim. Consider the investor's Euler equation for the consumption claim $E_t[M_{t+1}R^a_{t+1}] = 1$. This can be decomposed as:

$$1 = (1-p_t)E_t[\exp(\alpha \log \beta - \frac{\alpha}{\psi}\Delta c^{ND}_{t+1} + \alpha r^{ND}_{a,t+1})] + p_t E_t[\exp(\alpha \log \beta - \frac{\alpha}{\psi}\Delta c^{D}_{t+1} + \alpha r^{D}_{a,t+1})],$$

where ND (D) denotes the Gaussian (disaster) component of consumption growth, dividend growth or returns. We define "resilience" for the consumption claim as:

$$H^c_t = 1 + p_t\left(E_t\left[\exp\left\{(\gamma-1)J^c_{t+1}\right\}\right] - 1\right).$$

We log-linearize the total wealth return $R^a_{t+1} = \frac{W_{t+1}}{W_t - C_t}$ as follows: $r_{a,t+1} = \kappa^c_0 + wc_{t+1} - \kappa^c_1 wc_t + \Delta c_{t+1}$ with linearization constants:

$$\kappa^c_1 = \frac{e^{\overline{wc}}}{e^{\overline{wc}} - 1} \quad (3)$$

$$\kappa^c_0 = -\log\left(e^{\overline{wc}} - 1\right) + \kappa^c_1 \overline{wc}. \quad (4)$$

The wealth-consumption ratio differs across Markov states. Let wc_i be the log wealth-consumption ratio in Markov state i. The mean log wealth-consumption ratio can be computed using the stationary distribution:

$$\overline{wc} = \sum_{i=1}^{I} \Pi_i wc_i \quad (5)$$

where Π_i is the i^{th} element of vector Π. Note that the linearization constants κ_0^c and κ_1^c depend on $\overline{wc}$. Using the log linearization for the total wealth return, the Euler equation can be restated as follows:

$$1 = \exp(h_t^c) E_t \left[\exp \left\{ \alpha \log \beta - \frac{\alpha}{\psi}(\mu_c + \sigma_{ci}\eta_{t+1}) + \alpha(\kappa_0^c + wc_{t+1} - \kappa_1^c wc_t + \Delta c_{t+1}^{ND}) \right\} \right].$$

Resilience takes a simple form in our setting:

$$\begin{aligned} h_t^c &\equiv \log(H_t^c) = \log\left(1 + p_t\left[\exp\left\{\bar{h}^c\right\} - 1\right]\right), \\ \bar{h}^c &\equiv \log E_t\left[\exp\left\{(\gamma-1)J_{t+1}^c\right\}\right] = \omega\left(\exp\left\{(\gamma-1)\theta_c + .5(\gamma-1)^2\delta_c^2\right\} - 1\right), \end{aligned}$$

where we used the cumulant-generating function to compute $\bar{h}^c$. It is now clear that resilience only varies with the probability of a disaster p_t. Therefore, it too is a Markov chain. Denote by h_i^c the log resilience in Markov state i. Solving the Euler equation for the consumption claim amounts to solving for the log wealth-consumption ratio in each state i. We obtain the following system of I equations, which can be solved for wc_i, $i = 1, \dots I$:

$$1 = \exp(h_i^c) \exp\left\{\alpha(\log\beta + \kappa_0^c) + (1-\gamma)\mu_c - \alpha\kappa_1^c wc_i + \frac{1}{2}(1-\gamma)^2\sigma_{ci}^2\right\} \sum_{j=1}^{N} \pi_{ij} \exp\left\{\alpha wc_j\right\}$$

where π_{ij} is the transition probability between states i and j. Taking logs on both sides we get the following system of equations which can be solved in conjunction with (3), (4), and (5):

$$0 = h_i^c + \alpha(\log\beta + \kappa_0^c) + (1-\gamma)\mu_c - \alpha\kappa_1^c wc_i + \frac{1}{2}(1-\gamma)^2\sigma_{ci}^2 + \log\sum_{j=1}^{N} \pi_{ij}\exp\left\{\alpha wc_j\right\}.$$

B.2 Valuing the Dividend Claim

The investor's Euler equation for the stock is $E_t[M_{t+1}R_{t+1}^d] = 1$, which can be decomposed as:

$$\begin{aligned} 1 = {} & (1-p_t)E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{ND} + (\alpha-1)r_{a,t+1}^{ND} + r_{d,t+1}^{ND})\right] \\ & + p_t E_t\left[\exp(\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{D} + (\alpha-1)r_{a,t+1}^{D} + r_{d,t+1}^{D})\right] \end{aligned}$$

If we define "resilience" for the dividend claim as:

$$H_t^d = 1 + p_t\left(E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right] - 1\right),$$

then the Euler equation simplifies to:

$$1 = H_t^d E_t\left[\exp\left\{\alpha\log\beta - \frac{\alpha}{\psi}\Delta c_{t+1}^{ND} + (\alpha-1)r_{a,t+1}^{ND} + r_{d,t+1}^{ND}\right\}\right].$$

We log-linearize the stock return on bank i, R_{t+1}^d, as $r_{d,t+1} = \kappa_0^d + \kappa_1^d pd_{t+1} - pd_t + \Delta d_{t+1}$, with the linearization constants:

$$\kappa_1^d = \frac{e^{\overline{pd}}}{1+e^{\overline{pd}}}, \tag{6}$$

$$\kappa_0^d = \log(1+e^{\overline{pd}}) - \kappa_1^d\overline{pd}. \tag{7}$$

To compute the resilience term, we proceed as before:

$$\begin{aligned} h_t^d &\equiv \log\left(1 + p_t\left(\exp\left\{\bar{h}_d\right\} - 1\right)\right), \\ \bar{h}_d &\equiv \log E_t\left[\exp\left\{\gamma J_{t+1}^c - J_{t+1}^d - \lambda_d J_{t+1}^a\right\}\right]. \end{aligned}$$

By using the independence of the three jump processes conditional on a given number of jumps, we can simplify the last term to:

$$\begin{aligned} \bar{h}_d &= \log\left(\sum_{n=0}^{\infty} \frac{e^{-\omega}\omega^n}{n!} e^{n(\gamma\theta_c + .5\gamma^2\delta_c^2)} e^{n(-\theta_d + .5\delta_d^2)}\right. \\ &\quad \left. \times \left\{ e^{n(-\lambda_d\theta_r + .5\lambda_d^2\delta_r^2)} \Phi\left(\frac{\underline{J} - n\theta_r + n\lambda_d\delta_r^2}{\sqrt{n}\delta_r}\right) + e^{-\lambda_d \underline{J}} \Phi\left(\frac{n\theta_r - \underline{J}}{\sqrt{n}\delta_r}\right)\right\}\right). \end{aligned}$$

The derivation uses Lemma 1 below. The last expression, while somewhat complicated, is straightforward to compute. In the no-bailout case ($\underline{J} \to +\infty$), the last exponential term reduces to $e^{n(-\lambda_d\theta_r + .5\lambda_d^2\delta_r^2)}$. The dynamics of h_t^d are fully determined by the dynamics of p_t, which follows a Markov chain. Denote by h_i^d the resilience in Markov state i.

Solving the Euler equation for the dividend claim amounts to solving for the log price-dividend ratio in each state i, pd_i. We can solve the following system of N equations for pd_i:

$$\begin{aligned} pd_i &= h_i^d + \alpha\log\beta - \gamma\mu_c + (\alpha - 1)\left(\kappa_0^c - \kappa_1^c wc_i\right) + \kappa_0^d + \mu_d + \frac{1}{2}(\phi_d - \gamma)^2\sigma_{ci}^2 + \frac{1}{2}\sigma_{di}^2 \\ &\quad + \log\left(\sum_{j=1}^{N} \pi_{ij} \exp\left\{(\alpha - 1)wc_j + \kappa_1^d pd_j\right\}\right), \end{aligned}$$

together with the linearization constants in (6) and (7), and the mean pd ratio:

$$\overline{pd} = \sum_j \Pi_j pd_j. \tag{8}$$

B.3 Dividend Growth and Return Variance, Return Covariance, and the Equity Risk Premium

Preliminaries Recall that dividend growth in state i today is

$$\begin{aligned} \Delta d_i &= (1 - p_i)\Delta d_i^{ND} + p_i \Delta d_i^D, \\ \Delta d_i^{ND} &= \mu_d + \phi_d\sigma_{ci}\eta + \sigma_{di}\epsilon, \\ \Delta d_i^D &= \mu_d + \phi_d\sigma_{ci}\eta + \sigma_{di}\epsilon - J^d - \lambda_d J^a \end{aligned}$$

where the shock $\epsilon = \sqrt{\xi_d}\epsilon^a + \sqrt{1 - \xi_d}\epsilon^i$ is the sum of a common shock and an idiosyncratic shock, both of which are standard normally distributed and i.i.d. over time. Stock returns in state i today and assuming a transition to state j next period are:

$$\begin{aligned}
r_i &= (1-p_i)r_i^{ND} + p_i r_i^D, \\
r_i^{ND} &= \mu_{rij} + \phi_d \sigma_{ci}\eta + \sigma_{di}\epsilon, \\
r_i^D &= \mu_{rij} + \phi_d \sigma_{ci}\eta + \sigma_{di}\epsilon - J^d - \lambda_d J^a, \\
\mu_{rij} &= \mu_d + \kappa_0^d + \kappa_1^d pd_j - pd_i, \\
J^a &= \min(J^r, \underline{J}).
\end{aligned}$$

We are interested in computing the variance of dividend growth rates, the variance of returns and the covariance between a pair of returns. This will allow us to compute the volatility of returns and the correlation of returns.

Applying Lemma 4 below to the J^a process and conditioning on n jumps, we get that

$$\begin{aligned}
E[J^a|n] &= E[\min(J^r, \underline{J})|n] \\
&= E[J^r 1_{(J^r<\underline{J})}|n] + \underline{J}E[1_{(J^r\geq\underline{J})}|n] \\
&= n\theta_r \Phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right) - \sqrt{n}\delta_r \phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right) + \underline{J}\Phi\left(\frac{n\theta_r-\underline{J}}{\sqrt{n}\delta_r}\right),
\end{aligned}$$

and

$$\begin{aligned}
E[J^{a2}|n] &= E[\min(J^r, \underline{J})^2|n] \\
&= E[J^{r2} 1_{(J^r<\underline{J})}|n] + \underline{J}^2 E[1_{(J^r\geq\underline{J})}|n] \\
&= \left(n\delta_r^2 + n^2\theta_r^2\right)\Phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right) - \sqrt{n}\delta_r(\underline{J}+n\theta_r)\phi\left(\frac{\underline{J}-n\theta_r}{\sqrt{n}\delta_r}\right) + \underline{J}^2\Phi\left(\frac{n\theta_r-\underline{J}}{\sqrt{n}\delta_r}\right).
\end{aligned}$$

Note that the corresponding moments for the J^d process are:

$$\begin{aligned}
E[J^d|n] &= n\theta_d \\
E[J^{d2}|n] &= n\delta_d^2 + n^2\theta_d^2.
\end{aligned}$$

We now average over all possible realizations of the number of jumps n to get:

$$\begin{aligned}
E[J^d] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^d|n] = \theta_d, \\
E[J^{d2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^{d2}|n] = \delta_d^2 + 2\theta_d^2, \\
E[J^a] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^a|n] \equiv \theta_a, \\
E[J^{a2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} E[J^{a2}|n], \\
E[J^d J^a] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n\theta_d E[J^a|n], \\
E[J^{d,1}J^{d,2}] &= \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} (n\theta_d)(n\theta_d) = 2\theta_d^2
\end{aligned}$$

where we used our assumption that $\omega = 1$, which implies that $\sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n = 1$ and $\sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} n^2 = 2$. The last but one expression uses the fact that the two jumps are uncorrelated, conditional on a given number of jumps. The last expression computes the expectation of the product of the idiosyncratic jumps for two different stocks. Note that the correlation between these two idiosyncratic jump processes is zero if and only if $\theta_d = 0$, an assumption we make in our calibration.

Dividend Growth and Return Volatility The variance of dividend growth of a firm can be computed as follows

$$\begin{aligned}
Var[\Delta d_i] &= (1-p_i)E[(\Delta d_i^{ND})^2] + p_i E[(\Delta d_i^{D})^2] - \left[(1-p_i)E[\Delta d_i^{ND}] + p_i E[\Delta d_i^{D}]\right]^2, \\
&= (1-p_i)\left[\mu_d^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\right] \\
&\quad + p_i\left[\mu_d^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + E[J^{d2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\mu_d(E[J^d] + \lambda_d E[J^a])\right] \\
&\quad - \left[(1-p_i)\mu_d + p_i[\mu_d - E[J^d] - \lambda_d E[J^a]]\right]^2, \\
&= \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + p_i(\delta_d^2 + 2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2
\end{aligned}$$

Similarly, mean dividend growth is given by $E[\Delta d_i] = \mu_d - p_i(\theta_d + \lambda_d\theta_a)$. If $\theta_d = 0$, as we assume, mean dividend growth is simply $\mu_d - p_i\lambda_d\theta_a$.

The variance of returns can be derived similarly, with the only added complication that we need to take into account state transitions from i to j that affect the mean return μ_{rij}.

$$\begin{aligned}
Var[r_i] &= (1-p_i)E[(r_i^{ND})^2] + p_i E[(r_i^{D})^2] - \left[(1-p_i)E[r_i^{ND}] + p_i E[r_i^{D}]\right]^2, \\
&= (1-p_i)\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\right] \\
&\quad + p_i\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + E[J^{d2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\sum_{j=1}^{I} \pi_{ij}\mu_{rij}(E[J^d] + \lambda_d E[J^a])\right] \\
&\quad - \left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij} - p_i(E[J^d] + \lambda_d E[J^a])\right]^2, \\
&= \zeta_{ri} + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2 + p_i(\delta_d^2 + 2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2,
\end{aligned}$$

where

$$\zeta_{ri} \equiv \sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 - \left(\sum_{j=1}^{I} \pi_{ij}\mu_{rij}\right)^2,$$

is an additional variance term that comes from state transitions that affect the price-dividend ratio. The volatility of the stock return is the square root of the variance.

Covariance of Returns The covariance of a pair of returns (r^1, r^2) in state i is:

$$\begin{aligned}
Cov[r_i^1, r_i^2] &= (1-p_i)E[r_i^{1,ND} r_i^{2,ND}] + p_i E[r_i^{1,D} r_i^{2,D}] \\
&\quad - \left[(1-p_i)E[r_i^{1,ND}] + p_i E[r_i^{1,D}]\right] \left[(1-p_i)E[r_i^{2,ND}] + p_i E[r_i^{2,D}]\right], \\
&= (1-p_i)\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d\right] \\
&\quad + p_i\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}^2 + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d + E[J^{d,1}J^{d,2}] + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a] - 2\sum_{j=1}^{I}\pi_{ij}\mu_{rij}(\theta_d + \lambda_d\theta_a)\right] \\
&\quad - \left(\sum_{j=1}^{I}\pi_{ij}\mu_{rij}\right)^2 - p_i^2(\theta_d + \lambda_d\theta_a)^2 + 2\sum_{j=1}^{I}\pi_{ij}\mu_{rij}(\theta_d + \lambda_d\theta_a), \\
&= \zeta_{ri} + \phi_d^2\sigma_{ci}^2 + \sigma_{di}^2\xi_d + p_i(2\theta_d^2 + \lambda_d^2 E[J^{a2}] + 2\lambda_d E[J^d J^a]) - p_i^2(\theta_d + \lambda_d\theta_a)^2,
\end{aligned}$$

where we recall that ξ_d is the fraction of the variance of the Gaussian ϵ shock that is common across all stocks. The correlation between two stocks is the ratio of the covariance to the variance (given symmetry).

Equity Risk premium By analogy with the derivations above, we have

$$\begin{aligned}
E[J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}E[J^c|n] = \theta_c, \\
E[J^d J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}(n\theta_d)(n\theta_d) = 2\theta_c\theta_d, \\
E[J^a J^c] &= \sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}n\theta_c E[J^a|n]
\end{aligned}$$

We also have

$$\begin{aligned}
m^{ND} &= \mu_{mij} - \gamma\sigma_{ci}\eta, \\
m^D &= \mu_{mij} - \gamma\sigma_{ci}\eta + \gamma J^c, \\
\mu_{mij} &= \alpha\log\beta + (\alpha-1)(\kappa_0^c + wc_j - \kappa_1^c wc_i) - \gamma\mu_c,
\end{aligned}$$

The equity risk premium is $-Cov(m, r)$, which can be derived similarly to the covariance between two returns. In particular:

$$
\begin{aligned}
Cov[m_i, r_i] &= (1-p_i)E[m_i^{ND} r_i^{ND}] + p_i E[m_i^D r_i^D] \\
&\quad - \left[(1-p_i)E[m_i^{ND}] + p_i E[m_i^D]\right] \left[(1-p_i)E[r_i^{ND}] + p_i E[r_i^D]\right], \\
&= (1-p_i)\left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}\mu_{mij} - \gamma\phi_d\sigma_{ci}^2\right] \\
&\quad + p_i \left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij}\mu_{mij} - \gamma\phi_d\sigma_{ci}^2 - \gamma E[J^d J^c] - \gamma\lambda_d E[J^a J^c] + \gamma \sum_{j=1}^{I} \pi_{ij}\mu_{rij}\theta_c - \sum_{j=1}^{I} \pi_{ij}\mu_{mij}(\theta_d + \lambda_d\theta_a)\right] \\
&\quad - \left[\sum_{j=1}^{I} \pi_{ij}\mu_{mij} + p_i\gamma\theta_c\right] \left[\sum_{j=1}^{I} \pi_{ij}\mu_{rij} - p_i(\theta_d + \lambda_d\theta_a)\right] \\
&= \zeta_{mi} - \gamma\phi_d\sigma_{ci}^2 - p_i\gamma(2\theta_d\theta_c + \lambda_d E[J^c J^a]) + p_i^2\gamma\theta_c(\theta_d + \lambda_d\theta_a),
\end{aligned}
$$

where

$$
\zeta_{mi} \equiv \sum_{j=1}^{I} \pi_{ij}\mu_{rij}\mu_{mij} - \left(\sum_{j=1}^{I} \pi_{ij}\mu_{rij}\right)\left(\sum_{j=1}^{I} \pi_{ij}\mu_{mij}\right).
$$

B.4 Valuing Options

The main technical contribution of the paper is to price options in the presence of a bailout guarantee. We are interested in the price per dollar invested in a put option (cost per dollar insured) on a bank stock. For simplicity, we assume that the option has a one-period maturity and is of the European type. We denote the put price by Put:

$$
Put_t = E_t\left[M_{t+1}\left(K - R_{t+1}\right)^+\right] = (1-p_t)Put_t^{ND} + p_t Put_t^D,
$$

where the strike price K is expressed as a fraction of a dollar (that is, $K = 1$ is the ATM option). The put price is the sum of a disaster component and a non-disaster component. We derive both components below. But first, we state and prove two important lemmas which are invoked repeatedly to derive the option prices.

B.4.1 Auxiliary Lemmas

Lemma 1. *Let $x \sim N(\mu_x, \sigma_x^2)$ and $y \sim N(\mu_y, \sigma_y^2)$ with $Corr(x, y) = \rho_{xy}$. Then*

$$
E[\exp(ax + by)1_{c>y}] = \Psi(a, b; x, y)\Phi\left(\frac{c - \mu_y - b\sigma_y^2 - a\rho_{xy}\sigma_x\sigma_y}{\sigma_y}\right) \tag{9}
$$

where $\Psi(a, b; x, y) = \exp\left(a\mu_x + b\mu_y + \frac{a^2\sigma_x^2}{2} + \frac{b^2\sigma_y^2}{2} + ab\rho_{xy}\sigma_x\sigma_y\right)$ is the bivariate normal moment-generating function of x and y evaluated at (a, b).

Proof. Lemma 1 First, note that $x|y \sim N\left(\mu_x + \frac{\rho_{xy}\sigma_x}{\sigma_y}[y - \mu_y], \sigma_x^2(1 - \rho_{xy}^2)\right)$, therefore

$$
E[\exp(ax)|y] = Q\exp\left(\frac{a\rho_{xy}\sigma_x}{\sigma_y}y\right)
$$

where $Q = \exp\left(a\mu_x - \frac{a\rho_{xy}\sigma_x\mu_y}{\sigma_y} + \frac{a^2\sigma_x^2(1-\rho_{xy}^2)}{2}\right)$. Denote $\Gamma = E[\exp(ax+by)1_{c>y}]$, then:

$$
\begin{aligned}
\Gamma &= E[E\{\exp(ax)|y\}\exp(by)1_{c>y}] \\
&= QE\left[\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b\right\}\right)1_{c>y}\right] \\
&= Q\int_{-\infty}^{c}\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b\right\}\right)dF(y) \\
&= Q\int_{-\infty}^{c}\exp\left(y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b+\frac{\mu_y}{\sigma_y^2}\right\}-\frac{y^2}{2\sigma_y^2}-\frac{\mu_y^2}{2\sigma_y^2}\right)\frac{dy}{\sigma_y\sqrt{2\pi}} \\
&\quad \text{Complete the square} \\
&= Q\exp\left(\frac{\sigma_y^2}{2}\sigma_y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b\right\}^2+\mu_y\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b\right\}\right)\int_{-\infty}^{c}\exp\left(-\frac{\left[y-\sigma_y^2\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b+\frac{\mu_y}{\sigma_y^2}\right\}\right]^2}{2\sigma_y^2}\right)\frac{dy}{\sigma_y\sqrt{2\pi}} \\
&\quad \text{Substitute } u = \frac{y-\sigma_y^2\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b+\frac{\mu_y}{\sigma_y^2}\right\}}{\sigma_y},\ du\sigma_y = dy \\
&= \exp\left(a\mu_x+\frac{a^2\sigma_x^2(1-\rho_{xy}^2)}{2}+\frac{\sigma_y^2}{2}\left\{\frac{a\rho_{xy}\sigma_x}{\sigma_y}+b\right\}^2+b\mu_y\right)\Phi\left(\frac{c-b\sigma_y^2-a\rho_{xy}\sigma_x\sigma_y-\mu_y}{\sigma_y}\right)
\end{aligned}
$$

□

Lemma 2. *Let $x \sim N(\mu_x, \sigma_x^2)$, then*

$$
E\left[\Phi\left(b_0+b_1x\right)\exp\left(ax\right)1_{x<c}\right] = \Phi\left(\frac{b_0-t_1}{\sqrt{1+b_1^2\sigma_x^2}}, \frac{c-t_2}{\sigma_x}; \rho\right)\exp(z_1) \tag{10}
$$

where $t_1 = -b_1t_2$, $t_2 = a\sigma_x^2+\mu_x$, $z_1 = \frac{a^2\sigma_x^2}{2}+a\mu_x$, $\rho = \frac{-b_1\sigma_x}{\sqrt{1+b_1^2\sigma_x^2}}$, and $\Phi(\cdot\ ,\cdot\ ;\rho)$ is the cumulative density function (CDF) of a bivariate standard normal with correlation parameter ρ.

Proof. Lemma 2 Denote $\Omega = E\left[\Phi\left(b_0 + b_1 x\right)\exp\left(ax\right)1_{x<c}\right]$, then:

$$\begin{aligned}
\Omega &= \int_{-\infty}^{c}\int_{-\infty}^{b_0+b_1x}\exp\left(ax\right)dF(v)dF(x) \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0+b_1x}\exp\left(ax - \frac{v^2}{2} - \frac{\left[x-\mu_x\right]^2}{2\sigma_x^2}\right)\frac{dv\ dx}{\sigma_x 2\pi} \\
&\quad \text{Substitute } v = u + b_1 x,\ dv = du \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0}\exp\left(ax - \frac{(u+b_1x)^2}{2} - \frac{\left[x-\mu_x\right]^2}{2\sigma_x^2}\right)\frac{du\ dx}{\sigma_x 2\pi} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0}\exp\left(-\frac{u^2}{2} - x^2\left(\frac{1}{2\sigma_x^2} + \frac{b_1^2}{2}\right) - b_1 ux + 0u + x\left(a + \frac{\mu_x}{\sigma_x^2}\right) - \frac{\mu_x^2}{2\sigma_x^2}\right)\frac{du\ dx}{\sigma_x 2\pi} \\
&\quad \text{Complete the square in two variables using Lemma 3} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0}\exp\left\{\begin{pmatrix} u-t_1 \\ x-t_2 \end{pmatrix}'\begin{pmatrix} s1 & s2 \\ s2 & s3 \end{pmatrix}\begin{pmatrix} u-t_1 \\ x-t_2 \end{pmatrix} + z_1\right\}\frac{du\ dx}{\sigma_x 2\pi} \\
&= \int_{-\infty}^{c}\int_{-\infty}^{b_0}\exp\left(-\frac{1}{2}(U-T)'(-2S)(U-T) + z_1\right)\frac{du\ dx}{\sigma_x 2\pi}
\end{aligned}$$

where $U = (u,x), T = (t_1,t_2), -2S = \begin{pmatrix} 1 & b_1 \\ b_1 & b_1^2 + \frac{1}{\sigma_x^2} \end{pmatrix}, (-2S)^{-1} = \begin{pmatrix} 1 + b_1^2\sigma_x^2 & -b_1\sigma_x^2 \\ -b_1\sigma_x^2 & \sigma_x^2 \end{pmatrix}$. This is the CDF for $U \sim N(T,(-2S)^{-1})$. Let $w_1 = \frac{u-t_1}{\sqrt{1+b_1^2\sigma_x^2}}$, $w_2 = \frac{x-t_2}{\sigma_x}$, and $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$ with $\rho = \frac{-b_1\sigma_x}{\sqrt{1+b_1^2\sigma_x^2}}$. We have that $W' = (w_1,w_2) \sim N(0,\Sigma)$. Also, $du = dw_1\sqrt{1+b_1^2\sigma_x^2}$ and $dx = dw_2\sigma_x$.

$$\begin{aligned}
\Omega &= \exp(z_1)\left\{\int_{-\infty}^{\frac{c-t_2}{\sigma_x}}\int_{-\infty}^{\frac{b_0-t_1}{\sqrt{1+b_1^2\sigma_x^2}}}\exp\left(-\frac{1}{2}W'\Sigma^{-1}W\right)\frac{dw_1\ dw_2}{2\pi\sqrt{1-\rho^2}}\right\}\sqrt{1+b_1^2\sigma_x^2}\sqrt{1-\rho^2} \\
&= \Phi\left(\frac{b_0-t_1}{\sqrt{1+b_1^2\sigma_x^2}}, \frac{c-t_2}{\sigma_x}; \rho\right)\exp(z_1)
\end{aligned}$$

where we used that $\sqrt{1+b_1^2\sigma_x^2}\sqrt{1-\rho^2} = 1$, and where completing the square implies $t_1 = -b_1 t_2$, $t_2 = a\sigma_x^2 + \mu_x$, $s_1 = -.5$, $s_2 = -.5b_1$, $s_3 = -.5b_1^2 - \frac{1}{2\sigma_x^2}$, and $z_1 = \frac{a^2\sigma_x^2}{2} + a\mu_x$ by application of Lemma 3. □

Lemma 3. *Bivariate Complete Square*

$$Ax^2 + By^2 + Cxy + Dx + Ey + F = \begin{pmatrix} x-t_1 \\ y-t_2 \end{pmatrix}'\begin{pmatrix} s_1 & s_2 \\ s_2 & s_3 \end{pmatrix}\begin{pmatrix} x-t_1 \\ y-t_2 \end{pmatrix} + z_1$$

where

$$\begin{aligned}
t_1 &= -(2BD - CE)/(4AB - C^2) \qquad s_1 = A \\
t_2 &= -(2AE - CD)/(4AB - C^2) \qquad s_2 = C/2 \\
z_1 &= F - \frac{BD^2 - CDE + AE^2}{4AB - C^2} \qquad s_3 = B.
\end{aligned}$$

The following lemma will be useful in deriving the variance and covariances of stock returns.

Lemma 4. *Let $Z \sim N(\mu, \sigma^2)$ and define $\phi = \phi\left(\frac{b-\mu}{\sigma}\right)$ and $\Phi = \Phi\left(\frac{b-\mu}{\sigma}\right)$. Then*

$$\begin{aligned} E[Z1_{Z<b}] &= \mu\Phi - \sigma\phi, && (11) \\ E[Z^2 1_{Z<b}] &= \left(\sigma^2 + \mu^2\right)\Phi - \sigma(b+\mu)\phi && (12) \end{aligned}$$

Proof.

$$E[Z1_{Z<b}] = E[Z|Z<b]Pr(Z<b) = \left(\mu - \frac{\sigma\phi}{\Phi}\right)\Phi = \mu\Phi - \sigma\phi$$

The second result is shown similarly:

$$\begin{aligned} E[Z^2 1_{Z<b}] &= E[Z^2|Z<b]Pr(Z<b) \\ &= (Var[Z^2|Z<b] + E[Z|Z<b]^2)Pr(Z<b) \\ &= \left(\sigma^2 - \frac{\sigma(b-\mu)\phi}{\Phi} - \sigma^2\frac{\phi^2}{\Phi^2} + \left[\mu - \frac{\sigma\phi}{\Phi}\right]^2\right)\Phi \\ &= \left(\sigma^2 + \mu^2\right)\Phi - \sigma(b+\mu)\phi. \end{aligned}$$

□

B.4.2 Option Prices Conditional on No Disaster

Conditional on no disaster in the next period, we are back to the familiar Black-Scholes world (with Epstein-Zin preferences). The option value in state i is:

$$\begin{aligned} Put_i^{ND} &= E\left[M^{ND}(K - R^{ND})^+\right] \\ &= -E\left[\exp\left(m^{ND} + r^{ND}\right)1_{k>r^{ND}}\right] + KE\left[\exp\left(m^{ND}\right)1_{k>r^{ND}}\right] \end{aligned}$$

We condition on a Markov state transition from state i in the current period to state j in the next one. Then, the log SDF and log return are bivariate normally distributed; see Appendices B.3 and B.3. Application of Lemma 1 in Appendix B.4.1 leads to the familiar Black-Scholes value of a put option:

$$Put_{ij}^{ND} = -\Psi(1,1;m^{ND},r^{ND})\Phi(d_{ij} - \sigma_{ri}) + Ke^{-r_{ij}^{f,ND}}\Phi(d_{ij}), \quad (13)$$

where $d_{ij}^{ND} = \frac{k - \mu_{rij} - \sigma_{m,r}}{\sigma_{ri}}$, where $k = \log(K)$, μ_{rij} is the mean log stock return conditional on a transition from i to j and no disaster, σ_{ri} is the volatility of the log stock return in state i, σ_{mr} is the covariance of the log return and log SDF, and where $\Psi(a,b;x,y) = \exp\left(a\mu_x + b\mu_y + \frac{a^2\sigma_x^2}{2} + \frac{b^2\sigma_y^2}{2} + ab\rho_{xy}\sigma_x\sigma_y\right)$ is the bivariate normal moment-generating function of x and y evaluated at (a,b). We have used the fact that $\Psi(1,0;m^{ND},r^{ND}) = \exp(\mu_{mj} + .5\sigma_m^2) = \exp(-r_{ij}^{f,ND})$, where $r_{ij}^{f,ND}$ is the risk-free rate in Markov state i, conditional on a transition to state j and conditional on no disaster. As an aside, if there were no disaster state, then $\Psi(1,1;m^{ND},r^{ND}) = 1$.[21] Since we conditioned on a particular transition to state j, we still

[21] This would follow immediately from the fact that the no-disaster return would satisfy the Euler equation in this case. We would then have that $\mu_r = r^{f,ND} - \sigma_{m,r} - .5\sigma_r^2$ with $-\sigma_{m,r} = \gamma\phi\sigma_{ci}^2$ as the familiar Gaussian equity risk premium. Equation (13) would therefore collapse to the standard Black-Scholes formula, with $d^{ND} = \frac{k - r^{f,ND} + .5\sigma_r^2}{\sigma_r}$.

have to average over all such transitions to obtain the no-disaster option price in state i:

$$Put_i^{ND} = \sum_{j=1}^{I} \pi_{i,j} Put_{ij}^{ND}.$$

B.4.3 Option Prices Conditional on a Disaster

Conditional on having a disaster, the formulae become substantially more involved due to the presence of a bailout option. Backus, Chernov, and Martin (2011) derive option prices in a setting similar to ours, but one that does not have the bailout option. In their setting, Black-Scholes can be applied because log returns are a Poisson mixtures of normals, so that they are normally distributed conditional on a given number of jumps. Option prices are then weighted-averages of Black-Scholes values, weighted by the Poisson probability of a given number of jumps. In the presence of the bailout option, log stock returns are no longer normally distributed; They contain a term $J^a = \min(J^r, \underline{J})$, where J^r is normal conditional on a given number of jumps so that J^a is not normal. A technical contribution of the paper is to show that we can still obtain closed-form expressions for the put option price. The result hinges on repeated application of Lemmas 1 and 2, stated in Appendix B.4.1. The details of the derivation are relegated to Appendix B.4.3.

We start by conditioning on a Markov state transition from state i to state j and we condition on n jumps to the three jump processes (J^c, J^i, J^r). The option value is

$$\begin{aligned} Put_{ijn}^D &= E\left[M^D(K - R^D)^+\right] \\ &= -E\left[\exp\left(m^D + r^D\right) 1_{k>r^D}\right] + KE\left[\exp\left(m^D\right) 1_{k>r^D}\right], \\ &= -Put_{ijn1}^D + Put_{ijn2}^D. \end{aligned}$$

We define the random variable $\tilde{r} = r^{ND} - J^d$. Log returns in the disaster state are $r^D = \tilde{r} - \lambda_d J^a$. The appendix derives the following expressions for the two terms in the put price:

$$\begin{aligned} Put_{ijn1}^D = &\left\{ e^{n(-\lambda_d\theta_r + .5\lambda_d^2\delta_r^2)} \Phi\left(\frac{k - \mu_{rij} + n\theta_i - \sigma_{\tilde{r}}^2 - \sigma_{m^D,\tilde{r}} + n(\lambda_d\theta_r - \lambda_d^2\delta_r^2)}{\sqrt{\sigma_{\tilde{r}}^2 + n\lambda_d\delta_r^2}}, \frac{\underline{J} - n\theta_r + n\lambda_d\delta_r^2}{\sqrt{n}\delta_r}; \rho \right) \right. \\ &\left. + e^{-\lambda_d\underline{J}} \Phi\left(\frac{\lambda_d\underline{J} + k - \mu_{rij} + n\theta_i - \sigma_{\tilde{r}}^2 - \sigma_{m^D,\tilde{r}}}{\sigma_{\tilde{r}}} \right) \Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}} \right) \right\} \Psi(1, 1; m^D, \tilde{r}) \end{aligned} \tag{14}$$

$$\begin{aligned} Put_{ijn2}^D = &\ Ke^{-r_{ijn}^{f,D}} \left\{ \Phi\left(\frac{k - \mu_{rij} + n\theta_i - \sigma_{m^D,\tilde{r}} + n\lambda_d\theta_r}{\sqrt{\sigma_{\tilde{r}}^2 + n\lambda_d^2\delta_r^2}}, \frac{\underline{J} - n\theta_r}{\sqrt{n}\delta_r}; \rho \right) \right. \\ &\left. + \Phi\left(\frac{\lambda_d\underline{J} + k - \mu_{rij} + n\theta_i - \sigma_{m^D,\tilde{r}}}{\sigma_{\tilde{r}}} \right) \Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}} \right) \right\} \end{aligned} \tag{15}$$

We note that $\Psi(1, 0; m^D, \tilde{r}) = e^{-r_{ijn}^{f,D}}$, where $r_{ijn}^{f,D}$ is the risk-free rate conditional on a disaster realization, n jumps, and a Markov transition from state i to j. The correlation coefficient is:

$$\rho = -\frac{\sqrt{n}\lambda_d\delta_r}{\sqrt{\sigma_r^2 + n\delta_i^2 + n\lambda_d^2\delta_r^2}}.$$

Note that equations (14) and (15) are entirely in terms of the structural parameters of the model. Thus, we essentially obtain closed-form solutions for the option prices.

Finally, we sum over the various jump events and Markov states j to obtain the disaster option price in state i:

$$Put_i^D = \sum_{j=1}^{I} \pi_{i,j} \sum_{n=1}^{\infty} \frac{e^{-\omega}\omega^n}{n!} \left(-Put_{ijn1}^D + Put_{ijn2}^D\right). \tag{16}$$

Derivation We condition on the disaster state occurring in the next period, on a transition from state i to state j and on a known number of jumps n for the jump variables. Later we will average over the possible values for each. The put option value in this state is:

$$\begin{aligned} Put_{ijn}^D &= E\left[M^D(K - R^D)1_{K>R^D}\right] \\ &= -E\left[\exp\left(m^D + r^D\right)1_{k>r^D}\right] + KE\left[\exp\left(m^D\right)1_{k>r^D}\right] \\ &= -Put_{ijn1}^D + Put_{ijn2}^D. \end{aligned}$$

We now develop the two terms. For ease of notation, let $V_1^D = Put_{ijn1}^D$ and $V_2^D = Put_{ijn2}^D$.

Recall that $\tilde{r} = r^{ND} - J_i$ and $r^D = \tilde{r} - \lambda_d \min(J^r, \underline{J})$. Our derivation below exploits the normality of the following two random variables:

$$\begin{aligned} m^D &= \mu_{mij} - \gamma\sigma_{ci}\eta + \gamma J_c \sim N(\mu_m + \gamma n\theta_c, \sigma_m^2 + \gamma^2 n\delta_c^2) \\ \tilde{r} &= \mu_{rij} + \phi\sigma_{ci}\eta + \sigma_{di}\epsilon - J^i \sim N(\mu_{rj} - n\theta_i, \sigma_{\tilde{r}}^2) \\ \sigma_{\tilde{r}}^2 &= \sigma_r^2 + n\delta_i^2, \quad \sigma_{m^D,\tilde{r}} = \sigma_{m,r} = -\gamma\phi\sigma_{ci}^2 \end{aligned}$$

First term V_1^D

$$\begin{aligned} V_1^D &= E\left[\exp\left(m^D + r^D\right)1_{k>r^D}1_{J^r<\underline{J}}\right] + E\left[\exp\left(m^D + r^D\right)1_{k>r^D}1_{J^r>\underline{J}}\right] \\ &= E\left[\exp\left(m^D + r^{ND} - J_i - \lambda_d J^r\right)1_{k>r^D}1_{J^r<\underline{J}}\right] + E\left[\exp\left(m^D + r^{ND} - J_i - \lambda_d\underline{J}\right)1_{k>r^D}1_{J^r>\underline{J}}\right] \\ &= V_{11}^D + V_{12}^D \end{aligned}$$

The first term V_{11}^D can be solved as follows:

$$\begin{aligned} V_{11}^D &= E\left[\exp\left(m^D + \tilde{r} - \lambda_d J^r\right)1_{k>r^D}1_{J^r<\underline{J}}\right] \\ &= E\left[E\left\{\exp\left(m^D + \tilde{r} - \lambda_d J^r\right)1_{k+\lambda_d J^r>\tilde{r}}|J^r\right\} \mid 1_{J^r<\underline{J}}\right] \\ &= E\left[E\left\{\exp\left(m^D + \tilde{r}\right)1_{k+\lambda_d J^r>\tilde{r}}|J^r\right\}\exp\left(-\lambda_d J^r\right)1_{J^r<\underline{J}}\right] \\ &= \Psi(1,1;m^D,\tilde{r})E\left[\Phi\left(\phi_0 + \phi_1 J^r\right)\exp\left(-\lambda_d J^r\right)1_{J^r<\underline{J}}\right] \quad \text{by Lemma 1} \\ &= \Psi(1,1;m^D,\tilde{r})\exp(z_1)\Phi\left(\frac{\phi_0 - t_1}{\sqrt{1+\phi_1^2 n\delta_r^2}}, \frac{\underline{J} - t_2}{\sqrt{n}\delta_r}; \rho\right) \quad \text{by Lemma 2} \end{aligned}$$

where $\phi_1 = \frac{\lambda_d}{\sigma_{\tilde{r}}}$, $\phi_0 = \frac{\phi_1}{\lambda_d}\left(k - \mu_{rij} + n\theta_i - \sigma_{\tilde{r}}^2 - \sigma_{m^D,\tilde{r}}\right)$, $t_2 = n(\theta_r - \lambda_d\delta_r^2)$, $t_1 = -\phi_1 t_2$, $\rho = \frac{-\phi_1\sqrt{n}\delta_r}{\sqrt{1+\phi_1^2 n\delta_r^2}}$, and $z_1 = \frac{n\lambda_d^2\delta_r^2}{2} - n\lambda_d\theta_r$.

Next, we turn to V_{12}^D:

$$\begin{aligned} V_{12}^D &= E\left[\exp\left(m^D + r^{ND} - J_i - \lambda_d \underline{J}\right) 1_{k>r^D} 1_{J^r>\underline{J}}\right] \\ &= \exp(-\lambda_d \underline{J}) E\left[\exp\left(m^D + \tilde{r}\right) 1_{k+\lambda_d \underline{J}>\tilde{r}}\right] \Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}}\right) \\ &= \Psi(1,1;m^D,\tilde{r})\exp(-\lambda_d \underline{J})\Phi\left(\frac{\lambda_d \underline{J} + k - \mu_{rij} + n\theta_i - \sigma_{\tilde{r}}^2 - \sigma_{m^D,\tilde{r}}}{\sigma_{\tilde{r}}}\right)\Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}}\right) \quad \text{by Lemma 1.} \end{aligned}$$

Second term V_2^D

$$\begin{aligned} V_2^D &= KE\left[\exp\left(m^D\right) 1_{k>r^D}\right] \\ &= KE\left[\exp\left(m^D\right) 1_{k>r^D} 1_{J^r<\underline{J}}\right] + KE\left[\exp\left(m^D\right) 1_{k>r^D} 1_{J^r>\underline{J}}\right] \\ &= V_{21}^D + V_{22}^D. \end{aligned}$$

The first term V_{21}^D can be solved as follows:

$$\begin{aligned} V_{21}^D &= KE\left[\exp\left(m^D\right) 1_{k>r^D} 1_{J^r<\underline{J}}\right] \\ &= KE\left[E\left\{\exp\left(m^D\right) 1_{k+\lambda_d J^r>\tilde{r}} | J^r\right\} 1_{J^r<\underline{J}}\right] \\ &= K\Psi(1,0;m^D,\tilde{r})E\left[\Phi\left(\phi_0 + \phi_1 J^r\right) 1_{J^r<\underline{J}}\right] \quad \text{by Lemma 1} \\ &= K\Psi(1,0;m^D,\tilde{r})\Phi\left(\frac{\phi_0 - t_1}{\sqrt{1+\phi_1^2 n\delta_r^2}}, \frac{\underline{J} - t_2}{\sqrt{n}\delta_r}; \rho\right) \quad \text{by Lemma 2} \end{aligned}$$

where $\phi_1 = \frac{\lambda_d}{\sigma_{\tilde{r}}}$, $\phi_0 = \frac{\phi_1}{\lambda_d}\left(k - \mu_{rij} + n\theta_i - \sigma_{m^D,\tilde{r}}\right)$, $t_2 = n\theta_r$, $t_1 = -\phi_1 t_2$, $\rho = \frac{-\phi_1\sqrt{n}\delta_r}{\sqrt{1+\phi_1^2 n\delta_r^2}}$, and $z_1 = 0$. Because $z_1 = 0$, $\exp(z_1) = 1$, and we have dropped that term from the expression.

Finally, we turn to V_{22}^D:

$$\begin{aligned} V_{22}^D &= KE\left[\exp\left(m^D\right) 1_{k>r^D} 1_{J^r>\underline{J}}\right] \\ &= KE\left[\exp\left(m^D\right) 1_{k+\lambda_d \underline{J}>\tilde{r}} 1_{J^r>\underline{J}}\right] \\ &= KE\left[\exp\left(m^D\right) 1_{k+\lambda_d \underline{J}>\tilde{r}}\right] \Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}}\right) \\ &= K\Psi(1,0;m^D,\tilde{r})\Phi\left(\frac{\lambda_d \underline{J} + k - \mu_{rij} + n\theta_i - \sigma_{m^D,\tilde{r}}}{\sigma_{\tilde{r}}}\right)\Phi\left(\frac{n\theta_r - \underline{J}}{\delta_r\sqrt{n}}\right) \quad \text{by Lemma 1.} \end{aligned}$$

B.4.4 Option Pricing Absent Bailout Guarantees

Absent bailout options (NB), $J^a = J^r$, and we obtain substantial simplification to the general formula. This special case arises as $\underline{J} \to +\infty$. In that case, the second terms of equations (14) and (15) are zero.

In both first terms, the bivariate CDF simplifies to a univariate CDF.

$$\begin{aligned}
Put_{ijn}^{D,NB} &= -\Psi(1,1;m^D,\tilde{r})e^{n(-\theta_r+.5\delta_r^2)}\Phi\left(d_{jn}^{NB}-\sqrt{\sigma_r^2+n(\delta_i^2+\lambda_d^2\delta_r^2)}\right)+K\Psi(1,0;m^D,\tilde{r})\Phi\left(d_{jn}^{NB}\right) \\
&= -\exp\left(\mu_{mj}+\mu_{rij}+.5\sigma_m^2+.5\sigma_r^2+\sigma_{m,r}+n(\gamma\delta_c-\theta_i-\theta_r)+.5n(\gamma^2\delta_c^2+\delta_i^2+\delta_r^2)\right) \\
&\quad \times\Phi\left(d_{jn}^{NB}-\sqrt{\sigma_r^2+n(\delta_i^2+\delta_r^2)}\right)+K\exp\left(\mu_{mj}+.5\sigma_m^2+n\gamma\delta_c+.5n\gamma^2\delta_c^2\right)\Phi\left(d_{jn}^{NB}\right) \\
&= \exp\left(n\gamma\delta_c+.5n\gamma^2\delta_c^2\right)\left\{-\Psi(1,1;m^{ND},r^{ND})\exp\left(n(-\theta_i-\theta_r)+.5n(\delta_i^2+\delta_r^2)\right)\right. \\
&\quad \left.\times\Phi\left(d_{jn}^{NB}-\sqrt{\sigma_r^2+n(\delta_i^2+\delta_r^2)}\right)+Ke^{-r_{ij}^{f,ND}}\Phi\left(d_{jn}^{NB}\right)\right\}
\end{aligned}$$

with

$$d_{jn}^{NB}=\frac{k-\mu_{rij}+n(\theta_i+\lambda_d\theta_r)-\sigma_{m^D,\tilde{r}}}{\sqrt{\sigma_r^2+n\delta_i^2+n\lambda_d^2\delta_r^2}}$$

This equation is the counter-part of the Black-Scholes formula in equation (13), except that the mean and volatility of returns are adjusted for the jumps. Indeed, absent bailout options, log returns are normally distributed conditional on a given number of jumps n. We note that the expression for d^{NB} is in terms of the moments of the risk-neutral distribution of log returns. In particular, the risk-neutral mean is

$$\mu_{rij}^*=\mu_{rij}-n(\theta_i+\lambda_d\theta_r)-(-\sigma_{m^D,\tilde{r}}).$$

Thus the risk-neutral mean of the jump size equals the physical mean ($\theta_i^*=\theta_i$ and $\theta_r^*=\theta_r$), which follows from the fact that the jump sizes of the J^r and the J^i processes are independent of those of aggregate consumption J^c. The risk-neutral variance of log returns is equal to the physical variance, as usual ($\sigma_r^*=\sigma_r$, $\delta_i^*=\delta_i$ and $\delta_r^*=\delta_r$). The risk-neutral jump intensity is increased from the physical one as follows: $\omega^*=\omega\exp\left(\gamma\theta_c+.5\gamma^2\delta_c^2\right)$. To see this, note that the term $\exp\left(n\gamma\delta_c+.5n\gamma^2\delta_c^2\right)$, which factors out of the put price, can be folded into the Poisson weights when we sum over all possible number of jumps as in equation (2):

$$\sum_{n=1}^{\infty}\frac{e^{-\omega}\omega^n}{n!}\exp\left(n(\gamma\theta_c+.5\gamma^2\delta_c^2)\right)\cdots=\sum_{n=1}^{\infty}\frac{e^{-\omega^*}\omega^{*n}}{n!}\cdots$$

We recover the formulae of Backus, Chernov, and Martin (2011).

C Robustness Appendix

C.1 Return Correlation Fit

While it avoids the decline in correlation of the model without bailout guarantees, our benchmark calibration does not generate enough of an increase in return correlation from the pre-crisis to the crisis period. Depending on whether one interprets the crisis as an elevated probability of a disaster or as the actual realization of a disaster, the model's return correlation in state 2 is 51.1% or 40.7%. Both are below the observed 57.6%. To improve on this, we estimate the four key parameters ($\underline{J},\theta_r,\delta_r,\delta_d$) so as to best match the put and call basket, index, and spread prices in pre-crisis and crisis (12 moments), as well as the volatility of individual and index returns and return correlations in pre-crisis and crisis (6 moments). We give the return correlation moment a higher weight in the optimization and interpret the crisis data as the actual realization of a disaster. Our best fitting calibration generates a correlation that matches the 45.8% in the pre-crisis period and that increases to 58.7% or 51.2% in state 2 depending on whether a disaster is more likely or actually realized, respectively. They straddle the observed 57.6%; see Table C. The option pricing fit deteriorates slightly, but the model is still able to capture the observed patterns in put and call spreads reasonably well; see Table B. Interestingly, the parameters in this calibration imply that 50% of the value of the financial sector is attributable to the bailout guarantee, just as in the benchmark calibration.

C.2 Moneyness

Options with different moneyness may be informative about the degree of Gaussian versus tail aggregate and idiosyncratic risk. To investigate this possibility, we recalibrate our model to best fit financial sector basket and index put option prices with moneyness $\Delta = 20$, 30, 40, and 50, and their basket-index spread in pre-crisis and crisis (4 moments each), alongside the return volatility and return correlation moments, for a total of 30 moments. Keeping the Gaussian volatility σ_d constant across states at 15% and keeping the fraction of it that is common at 0%, Panel B of Table D shows a reasonably good fit for the various put prices. However, the model overstates the basket put price in the pre-crisis and understates it in the crisis for at-the-money options. A much better fit is obtained when we allow the Gaussian volatility to rise from 14.5% in state 1 to 30% in state 2 while simultaneously increasing the fraction of Gaussian shocks that are common from 0% in state 1 to 30% in state 2. This implies more Gaussian dividend (and return) risk during the crisis and more of it common across firms. We then reoptimize over the other four structural parameters to best fit the 30 moments under consideration. While the loss rate in a disaster θ_a of 42.0% in logs or 34.3% in levels is similar to that of our benchmark model (46.5% in logs and 37.2% in levels), the parameters $\theta_r = 1.28$ and $\delta_r = .95$ are substantially higher while the bailout parameter $\underline{J} = .79$ is substantially lower. The amount of idiosyncratic tail risk, governed by $\delta_d = .36$, is also lower because there is now more idiosyncratic Gaussian risk. As a result of the higher aggregate tail risk parameters, our estimates of the cost-of-capital savings from the bailout guarantee go up substantially. Removing the bailout option would result in an increase of the equity risk premium by a factor of 3.3-3.5 (from 4.0% to 13.1% in state 1 and from 12.1% to 42.9% in state 2), as opposed to a factor 2 in our benchmark calibration. That suggests our benchmark numbers are conservative.

C.3 Three-state Model

We also consider a model with somewhat richer dynamics for the probability of a disaster. In particular we want to differentiate between the relatively mild crisis of the August 2007-August 2008 and April 2009-June 2009 and the sharp crisis of September 2008-March 2009. A 3-state Markov model allows us to capture the idea that, conditional on being in a mild crisis there is a chance of a substantial deterioration in the health of the financial sector. We leave the disaster probability in state 1 at 7% and set the disaster probability in state 2 to 14% and to 60% in state 3. The 3-state model has the same 13% unconditional disaster probability. The transition probability matrix is $\Pi =$[0.85, 0.15, 0; 0.506, 0.286, 0.208; 0, 0.5, 0.5]. Consumption volatility is 0.35% in state 1, 0.75% in state 2, and 1.5% in state 3. As in the benchmark 2-state model, we hold $\sigma_d = .15$ and $\xi_d = 0$ constant across states. We choose the remaining four parameters to best fit the usual put and call price, and return moments (27 moments). The model generates a large increase in put spread from 0.6 in state 1 to 1.2 in state 2 to 8.3 in state 3. In the data, the put spread increases from 0.8 pre-crisis to 2.7 in the mild crisis subsamples, and to 6.4 in the severe crisis. The model generates a decline in the call spread from 0.2 to -0.2 from pre-crisis to severe crisis, compared to 0.3 to -0.1 in the data. The model is also broadly consistent with the sharp increases in individual and index volatility during the severe crisis, and with the increase in return correlations in both crisis subsamples. Detailed results are available upon request. The model implies an equity risk premium of 5.6% pre-crisis, 21.4% in the mild crisis, and 29.2% in the severe crisis. Absent the bailout option, the risk premium would be 12.3, 39.2, and 73.2%; the value of the financial sector would be 45% lower.

C.4 Heterogeneity across Large and Small Banks

So far, we have considered models were all banks are ex-ante identical. One might think that large banks are more systemically risky and may therefore enjoy larger government guarantees. All else equal, that would result in comparatively lower costs of capital for large banks. To investigate this hypothesis, we consider two groups of banks. The first group consists of the largest ten banks by market capitalization as of the end of July 2007 (see right column of Table A) plus Fannie Mae (number 11) and Freddie Mac (number 14). We refer to this group as the "big 12." The second group contains all other banks in the financial sector index. When we loose a member of the big 12 in our option data set, we replace it the next-largest bank as of the end of July 2007. There are four such replacements (for Fannie and Freddie on September 8, 2008 and for Wachovia and Merrill Lynch on January 1, 2009) so that BNY-Mellon, US Bancorp, Metlife and Prudential join the big 12, in that order. The resulting big 12 group has a stable market share between 45 and 55% of the total market capitalization of all firms in the financial sector index over our sample. A sample without replacement would have a declining market share during the crisis. For these two groups of banks, we hold fixed all aggregate risk parameters $(\underline{J}, \theta_r, \delta_r, \sigma_c)$ at their values from the calibration discussed in Section C.1. We continue to set $\xi_d = 0$ so that all non-priced Gaussian dividend shocks are idiosyncratic. We allow for heterogeneity across the groups in the parameters $(\lambda_d, \delta_d, \sigma_d(1), \sigma_d(2))$. The first parameter governs how much exposure a bank has to the aggregate tail process J^a, the second its idiosyncratic tail risk, and the last two the Gaussian idiosyncratic risk. We set the parameter $\lambda_d = 1.208$ for large banks and $\lambda_d = 0.936$ for small banks in order to match the (within-group average) regression coefficients of individual stock returns on a constant and the financial sector index return using only the most extreme 10% of index returns on the downside. We recall that we normalized $\lambda_d = 1$ for the full sample of banks. Thus, the data suggest that large banks have more aggregate tail risk exposure than small banks. We choose the remaining three parameters for each group so that they are on opposite sides of the common parameter choice of Section C.1, and so that they best fit the return correlation and volatility and the put and call prices of the options for each group.

Panel A of Table E shows the observed put and call prices for the big 12 (Panel A.1) and the other banks (Panel A.2). They are the value-weighted averages within each group, taken over the two pre-crisis and crisis subsamples. They also indicate the put and call spreads, which subtract from the option basket the (common) index option price. Finally, the table reports the (value-weighted) average individual return volatility and pairwise correlation among the stocks within a group. From pre-crisis to crisis, the increase in return volatility and put spread are much larger for the big 12 than for the smaller banks while the increase in return correlation is much smaller. Panel B shows that our model can match these facts for both groups. In addition to a higher aggregate tail risk exposure, large banks have more idiosyncratic tail risk, which is needed to explain their high return volatility during the crisis, and less Gaussian idiosyncratic risk, which is needed to explain their high pre-crisis return correlation which increases only modestly during the crisis. The opposite is true for small banks; the parameter choices are listed in the table caption. Having shown that we can account for the heterogeneity in option price and return features of each group, we can ask how much higher the cost of capital would be for each group absent a bailout guarantee, holding fixed the other group-specific parameters. We find that the cost of capital for large banks would increase by 12% points, 1.5 times the 9% point increase for the small banks. This suggests that large banks' options were "cheap" because they disproportionately enjoyed the government guarantee.

Table A: Top 40 Holdings of the Financial Sector Index XLF

	12/30/2010		07/30/2007	
	Name	Weighting	Name	Weighting
1	JPMorgan Chase & Co.	9.01	CITIGROUP INC	11.1
2	Wells Fargo & Co.	8.86	BANK OF AMERICA CORP	10.14
3	Citigroup Inc.	7.54	AMERICAN INTERNATIONAL GROUP I	8.02
4	BERKSHIRE HATHAWAY B	7.52	JPMORGAN CHASE & Co	7.25
5	Bank of America Corp.	7.3	WELLS FARGO & Co NEW	5.44
6	Goldman Sachs Group Inc.	4.66	WACHOVIA CORP 2ND NEW	4.35
7	U.S. BANCORP	2.82	GOLDMAN SACHS GROUP INC	3.71
8	American Express Co.	2.44	AMERICAN EXPRESS CO	3.35
9	MORGAN STANLEY	2.25	MORGAN STANLEY DEAN WITTER & C	3.25
10	MetLife Inc.	2.21	MERRILL LYNCH & Co INC	3.11
11	Bank of New York Mellon Corp.	2.04	FEDERAL NATIONAL MORTGAGE ASSN	2.81
12	PNC Financial Services Group Inc.	1.75	U S BANCORP DEL	2.51
13	Simon Property Group Inc.	1.6	BANK OF NEW YORK MELLON CORP	2.32
14	Prudential Financial Inc.	1.56	METLIFE INC	2.15
15	AFLAC Inc.	1.45	PRUDENTIAL FINANCIAL INC	2
16	Travelers Cos. Inc.	1.39	FEDERAL HOME LOAN MORTGAGE COR	1.83
17	State Street Corp.	1.27	TRAVELERS COMPANIES INC	1.63
18	CME Group Inc. Cl A	1.18	WASHINGTON MUTUAL INC	1.61
19	ACE Ltd.	1.15	LEHMAN BROTHERS HOLDINGS INC	1.59
20	Capital One Financial Corp.	1.06	ALLSTATE CORP	1.56
21	BB&T Corp.	1	C M E GROUP INC	1.46
22	Chubb Corp.	0.99	CAPITAL ONE FINANCIAL CORP	1.41
23	Allstate Corp.	0.93	HARTFORD FINANCIAL SVCS GROUP	1.4
24	Charles Schwab Corp.	0.93	SUNTRUST BANKS INC	1.35
25	T. Rowe Price Group Inc.	0.89	STATE STREET CORP	1.28
26	Franklin Resources Inc.	0.87	A F L A C INC	1.23
27	AON Corp.	0.82	P N C FINANCIAL SERVICES GRP I	1.11
28	EQUITY RESIDENTIAL	0.81	REGIONS FINANCIAL CORP NEW	1.02
29	Marsh & McLennan Cos.	0.81	LOEWS CORP	1.02
30	SunTrust Banks Inc.	0.8	FRANKLIN RESOURCES INC	1.01
31	Ameriprise Financial Inc.	0.78	SCHWAB CHARLES CORP NEW	0.98
32	PUBLIC STORAGE	0.77	B B & T CORP	0.98
33	Vornado Realty Trust	0.74	FIFTH THIRD BANCORP	0.98
34	Northern Trust Corp.	0.73	CHUBB CORP	0.97
35	HCP Inc.	0.73	S L M CORP	0.97
36	Progressive Corp.	0.71	SIMON PROPERTY GROUP INC NEW	0.93
37	Loews Corp.	0.67	ACE LTD	0.91
38	Boston Properties Inc.	0.66	NATIONAL CITY CORP	0.82
39	Host Hotels & Resorts Inc.	0.64	COUNTRYWIDE FINANCIAL CORP	0.81
40	FIFTH THIRD BANCORP	0.64	LINCOLN NATIONAL CORP IN	0.79

This table reports the XLF weights on 12/30/2010 and 07/30/2007. On 12/30/2010, there were 81 companies in XLF; on 07/30/2007, there were 96 companies. This table reports the relative market capitalizations of the top 40 holdings of the index.

Table B: Option Prices in Economy Calibrated to Match Correlations

The table reports option prices and implied volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the financial sector index. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.39$, $\underline{J} = 0.84$, $\theta_r = 0.95$, and $\delta_r = 0.71$.

	Put Prices			Call Prices		
	Basket	Index	Spread	Basket	Index	Spread
			Panel I: Data			
pre-crisis	4.0	3.2	0.8	1.6	1.3	0.3
crisis	13.7	9.9	3.8	2.4	2.3	0.1
			Panel II: Model with Bailout			
pre-crisis	3.9	3.7	0.2	1.4	1.0	0.4
crisis	11.7	8.8	2.9	2.3	2.1	0.2

Table C: Returns in in Economy Calibrated to Match Correlations

The table reports realized volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the non-financial sector index. The crisis numbers for the model represent the unconditional moment in state 2, taking disasters into account probabilistically. The number *in italic* for the model report the moments in state 2 of the model *conditional* on a disaster realization. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.39$, $\underline{J} = 0.84$, $\theta_r = 0.95$, and $\delta_r = 0.71$.

	Index	**Individual Stocks**	
	Volatility	Volatility	Correlations
		Panel I: Data	
pre-crisis	11.9	18.1	45.8
crisis	43.8	72.9	57.6
		Panel II: Model without Bailout	
pre-crisis	17.9	24.7	45.8
crisis	31.5	39.7	58.7
	44.2	*59.8*	*51.2*

Table D: Option Prices and Returns by Option Moneyness

The table reports basket and index put option prices for puts with moneyness Δ = 20, 30, 40, and 50. It also reports realized volatility for the financial sector index, for its constituents, and pairwise correlations between the stocks in the non-financial sector index. Panel A is for the January 2003-June 2009 data. Panel B is for a model with parameters $\sigma_d(1) = \sigma_d(2) = 0.15$, $\xi_d(1) = \xi_d(2) = 0$, $\delta_d = 0.47$, $\underline{J} = 0.82$, $\theta_r = 1.2$, and $\delta_r = 0.95$. Panel C is for a model with parameters $\sigma_d(1) = 0.145$, $\sigma_d(2) = 0.30$, $\xi_d(1) = 0$, $\xi_d(2) = 0.30$, $\delta_d = 0.36$, $\underline{J} = 0.79$, $\theta_r = 1.28$, and $\delta_r = 0.95$. The crisis numbers for the model represent the unconditional moment in state 2, taking disasters into account probabilistically. The number *in italics* for the model report the moments in state 2 of the model *conditional* on a disaster realization.

	Puts Delta = 20			**Puts Delta = 30**			**Puts Delta = 40**			**Puts Delta = 50**			**Return moments**		
Panel A: Moments in Data															
	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Index vol	Indiv vol	Indiv Correl
pre-crisis	4.0	3.2	0.8	5.8	4.6	1.2	7.7	6.1	1.6	9.8	7.7	2.1	11.9	18.1	45.8
crisis	13.7	9.9	3.8	17.8	13.4	4.4	21.6	16.7	4.9	25.5	20.1	5.4	43.8	72.9	57.5
Panel B: Moments in Model with Bailout; fix Gaussian risk															
	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Index vol	Indiv vol	Indiv Correl
pre-crisis	4.0	3.8	0.2	5.7	5.1	0.5	8.3	6.4	1.9	12.4	8.7	3.7	18.0	25.4	41.5
crisis	12.8	9.3	3.5	16.0	13.6	2.4	18.8	16.6	2.1	21.8	18.7	3.0	31.9/*46.0*	42.1/*66.2*	52.3/*44.4*
Panel C: Moments in Model with Bailout; change Gaussian risk															
	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Basket	Index	Spread	Index vol	Indiv vol	Indiv Correl
pre-crisis	3.7	3.6	0.1	5.3	4.9	0.3	8.0	6.1	1.8	12.8	8.2	4.6	17.2	23.5	45.6
crisis	12.3	8.9	3.4	16.4	13.0	3.4	20.4	16.3	4.1	24.4	19.1	5.3	35.1/*46.6*	46.2/*62.9*	53.4/*51.4*

Table E: Heterogeneity: Option and Return Moments for Large and Small Banks

The table reports basket put and call prices for options with moneyness $\Delta = 20$ and maturity of one year, as well as the spread over the corresponding index option price with the same *Delta* and maturity. It also reports individual stock return volatility and pairwise return correlations for the firms within each group. The two groups of firms are discussed in the main text. Panel A is for the January 2003-June 2009 data. Panel B is for the model with common parameters $\underline{J} = 0.84$, $\theta_r = 0.95$, $\delta_r = 0.71$, and $\xi_d(1) = \xi_d(2) = 0$. The big 12 group of large banks has parameters $\lambda_d = 1.208$, $\sigma_d(1) = 0.11$, $\sigma_d(2) = 0.09$, $\delta_d = 0.50$. The group of all other banks has parameters $\lambda_d = 0.936$, $\sigma_d(1) = 0.18$, $\sigma_d(2) = 0.20$, $\delta_d = 0.32$. Within each group, all firms are ex-ante identical. The crisis numbers for the model represent the unconditional moment in state 2, taking disasters into account probabilistically. The number *in italics* for the model report the moments in state 2 of the model *conditional* on a disaster realization.

	Panel A: Data											
	Panel A.1: Big 12						Panel A.2: All other banks					
	Put prices		Call prices		Returns		Put prices		Call prices		Returns	
	basket	spread	basket	spread	indiv vol	correl	basket	spread	basket	spread	indiv vol	correl
pre-crisis	4.0	0.8	1.6	0.3	17.0	57.0	4.0	0.9	1.7	0.3	24.6	38.7
crisis	14.5	4.6	2.4	0.1	84.7	59.4	12.8	2.9	2.4	0.0	44.9	57.6
	Panel B: Model											
	Panel B.1: Big 12						Panel B.2: All other banks					
	Put prices		Call prices		Returns		Put prices		Call prices		Returns	
	basket	spread	basket	spread	indiv vol	correl	basket	spread	basket	spread	indiv vol	correl
pre-crisis	4.6	0.9	1.3	0.2	26.3	57.1	3.7	0.0	1.5	0.5	25.4	38.7
crisis	14.5	5.7	2.4	0.3	45.9	63.0	10.6	1.9	2.3	0.2	38.8	54.4
					72.3	*50.6*					*55.1*	*53.1*