How do Big Banks Evaluate Risk? Evidence from Capital Purchase Program

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Abstract

This paper empirically tests theories of the psychology of tail events, in particular prospect theory. We first present a model where banks are subject to the subjective expected loss constraint. Then, we estimate the probability weighting function from the asset pricing equation of the largest banks that were recapitalized under the Capital Purchase Program. When facing such rare events, banks demonstrate the coexistence of over- and underweighting of tail losses. Banks tend to overweight small probability losses during the financial distress and underweight the same when not exposed to insolvency risk. Before and during government interventions, big banks overweight losses of low probabilities and underweight losses of high probabilities, consistent with an inverse S-shaped probability weighting function of prospect theory. In contrast, after the recapitalization, we find banks' proneness to underweight tail events. The results suggest that this behavioral bias is linked to funding liquidity, prior gains and losses, market risk, market sentiment, and policy uncertainty.

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1 Introduction

A crucial ingredient in asset pricing models is an assumption about how investors evaluate risks. As rational decision theory under risk, expected utility theory assumes that investors assess risk by treating probabilities linearly. But over the years, economists and psychologists have identified risk attitudes that depart significantly from the predictions of expected utility, notably prospect theory of Tversky and Kahneman (1992). Both in laboratory settings and economic theory, people may display considerable risk aversion in some situations and have risk-seeking preferences in other circumstances.[1] According to prospect theory, conflicting risk attitudes can partly be rationalized by decision-makers who nonlinearly transform probabilities. The main idea of probability weighting is that people use decision weights that depart from the objective probabilities in systematic ways to guide their decisions. Most commonly, such distortions lead people to overweight small probabilities and underweight large probabilities. This raises an obvious question: are probability distortions stable, and can these help us better understand the evidence on market returns and prices?

In this paper, we present new evidence on these questions. With the onset of the Great Recession, the Troubled Asset Relief Program (TARP) was established to stabilize the US financial system. The core of the recapitalization plan under TARP was the Capital Purchase Program (CPP), under which liquidity constrained financial institutions would receive capital injections from Treasury. The fundamental question we ask is how big banks exposed to insolvency risk evaluate market losses? The answer to this question may have essential implications for prudential authorities when measuring capital requirements to absorb market losses of financial institutions. Understanding the risk attitudes and assessments of recapitalized large banks is a starting point in the direction of optimal capital requirements design.

To do so, the first part of the paper incorporates probability distortions into the standard consumption-based pricing framework: banks in our model derive utility from consumption levels but are subject to expected loss constraint. Our model specification is further motivated by the dual theory of choice under risk and probability distortions in Yaari (1987) and Tversky and Kahneman (1992). Specifically, banks are constrained to hold enough capital to cover subjective expected losses. As in prospect theory, when thinking about investing in the risky asset, banks mentally represent gains and losses they associate with taking the risk. Second, banks evaluate this representation – the distribution of gains and losses – to compute subjective expected losses. In our specification, banks distort probabilities consistent with prospect theory. Given a risk that banks are considering, they can be either risk-averse or risk-seeking in market losses. Using the asset pricing equation, we estimate parameters of the probability weighting function by the generalized method of moments. Therefore, the goal of this paper is to test prospect theory predictions in the asset pricing model of liquidity constrained banks by estimating the parameters characterizing the behavior of large recapitalized banks. The first question we ask is, do large banks overweight or underweight tail losses? The question we fur-

[1]More recently, O'Donoghue and Somerville (2018) summarize empirical evidence of alternative models of risk attitudes.

ther ask is which economic variables explain probability distortions? In other words, we seek to get a better understanding of why banks prefer to underweight or overweight losses. We focus on four groups of plausible factors, namely market risk, liquidity, investors sentiment, and uncertainty.

That said, this paper complements literature that estimates the probability weighting function of prospect theory. Mostly in experimental settings, a large body of research finds strong support for an inverse S-shaped probability weighting to be an accurate description of behavior under financial incentives (Abdellaoui (2000); Abdellaoui et al. (2005); Booij et al. (2010); Etchart-Vincent (2004); Fehr-Duda et al. (2006); Gonzalez and Wu (1999); Stott (2006); Tversky and Kahneman (1992)). Among seminal contributions, Gonzalez and Wu (1999) report participants' inclination to overweight small probabilities and underweight large probabilities in lottery context. Exploring heterogeneity margin, Bruhin et al. (2010) highlights considerable differences in individual risk-taking behavior. Approximately 20% participants behave as expected utility maximizer and treat probabilities linearly, while 80% evaluate risky prospects with nonlinear probability distortions. The potential significance of probability weighting outside the laboratory setting has only recently been recognized. In the financial market environment, Kliger and Levy (2009) show that call option data reveals probability weighting consistent with prospect theory. Using data on households' choice of deductible levels for property insurance policies, Sydnor (2010) finds evidence of substantial probability distortions. More precisely, their estimates imply that, when a household chooses an insurance policy, it strongly overweights the small likelihood of having to file a claim. Barseghyan et al. (2013) report that overweighting tail events plays a significant role in explaining the manifested risk aversion in deductible home and automobile insurance choices. Unlike aforementioned papers, the evaluation of tail events by large and systematically important financial institutions is the focal point of this paper.

In summary, our first result indicates co-existence of overweighting and underweighting of tail events. Instead of the stable weighting function, the fourfold pattern emerges. We obtain concave, convex, concave-convex, and convex-concave weighting functions during four periods. Before the Great Recession, the largest banks tended to underweight the probability of tail losses, which generates the convex shape. During market turmoil and amid the CPP recapitalization, banks overweight the likelihood of the worst possible scenario. Merging the crisis and pre-crisis period generates an inverted S-curve of prospect theory, while the weighting function is S-shaped following the CPP. The second result is that banks are risk-averse in losses before and during government intervention, and risk-seeking afterward. Thirdly, our results imply that in the period before and during the government recapitalization program, factors such as tail prior losses, market volatility, beta, systematic skewness, and market-wide investor sentiment exacerbate overweighting of large banks. Interbank funding illiquidity, bank-specific volatility, and prior gains have damping effects. Finally, economic policy and market uncertainty initially lead to underweighting and subsequently overweighting of market losses.

Our first result adds to the accumulating evidence on dynamic and context-dependent probability weighting. In salience theory of Bordalo et al. (2013), when market gains are salient, meaning larger or less likely than losses, investors' attention is drawn to positive market outcomes causing them to underweight losses and overweight gains. Conversely, investors are prone to overweight losses in situations of abnormal negative return realizations. Fehr-Duda et al. (2010) find that the probability weighting function is sensitive to rising stakes, but not utility function. When the size of lottery gains increases, participants became less optimistic and overweighted small probabilities of large gain to a lower degree. Epper and Fehr-Duda (2017) show both theoretically and empirically that probability weighting coupled with the timing of the consequences and uncertainty resolution can explain the coexistence of over and underweighting of rare extreme events. In a parsimonious way, it captures risk tolerance variations in response to the length of the delay and the perception of uncertainty resolution. When the passage of time is irrelevant, the probability weighting function results in an inverse S-shape. First, unfavorable tail events are overweighted when perceived to materialize in the short-run but may end up being underweighted when expected to take place in the distant future. Second, sequential resolution of uncertainty counteracts this effect, in that rare events are overweighted when uncertainty is perceived to unfold gradually over time and underweighted in one shot at a specific time in the future. Therefore, the convex or concave weighting function we find may be a consequence of how large banks perceive tail losses to be absorbed by equity over time.

Because banks in our sample underwent a recapitalization process as the government response to large losses that pushed banks near bankruptcy, our paper shares insights with the literature that investigates how prior losses affect risk preferences. This field of finance has produced contradictory empirical evidence. For example, following a loss, agents become either more risk-seeking (Andrade and Iyer (2009); Langer and Weber (2008)), or more risk-averse (Liu et al. (2010); Shiv et al. (2005)). However, recent evidence suggests that investors may respond differently to paper or realized losses. Imas (2016) demonstrate that participants take on more risk after a *paper* loss (if the loss has not been realized) and less risk after a realized loss. One explanation of why banks that suffered realized losses prior to government intervention, behave in a risk-seeking manner after the intervention is that recapitalization encourages banks to perceive realized losses as paper losses. In turn, paper loss leads to risk seeking.

Our third result contributes to the literature that applies probability weighting of prospect theory to asset pricing (e.g. Barberis and Huang (2008); Barberis et al. (2001,1); De Giorgi and Legg (2012); Fehr-Duda and Epper (2011)). Notably, Barberis et al. (2019) demonstrates that prospect theory helps explain 22 stock market anomalies. One of the predictions is that an asset's idiosyncratic volatility, skewness, and the average prior gain or loss will be priced and affect expected returns and equity premiums when investors evaluate risk according to prospect theory. From the empirical point, in addition to these three asset characteristics, we explore factors associated with liquidity, sentiment, and policy uncertainty that affect probability distortions and equity premium of recapitalized banks.

Given our findings, understanding risk attitudes in peaceful times versus distress periods may have vital implications for systemic risk and regulators. In macroprudential policy application, empirical evidence on perceptions of market losses before, during, and after the recent crisis can be used for the design of capital requirements over the business cycle or as an early warning indicator of crises. In particular, regulators may estimate probability weighting function in the tranquil period, especially for systemically important institutions, which can serve as an indicator of vulnerabilities in financial markets. Knowing how much market and banks underweight losses can give policymakers room to anticipate downturns and prepare response ex-ante when apparent market conditions are predictable. Such reasoning is consistent with Gennaioli et al. (2012) who suggest that when investors and financial intermediaries neglect downside tail risk because they cannot imagine worst-case outcomes during quiet times, systemic risk sharply increases. Second, the weighting function from the distress period can be used to compute expected loss and required level of capital requirements. By construction, such buffers take into account perceptions of banks and market participants in the midst of market turmoil, and in this way, might reduce the vulnerability of financial institutions to losses and improve their resilience. Thirdly, by differentiating which economic variables increase or decrease overweighting and underweighting, regulators can calibrate capital buffers to respond to, for instance, aggregate liquidity indicators.

The paper proceeds as follows. Section 2 briefly reviews probability weighting and outlines the asset pricing model with banks operating under expected loss constraint. Section 3 estimates the probability distortions of the largest banks. Section 4 investigates economic drivers of probability distortions. Section 5 concludes.

2 Theory

In this section, we briefly define probability weighting function and spectral risk measures, which will be used in section 3.3 to derive and estimate the asset pricing equation.

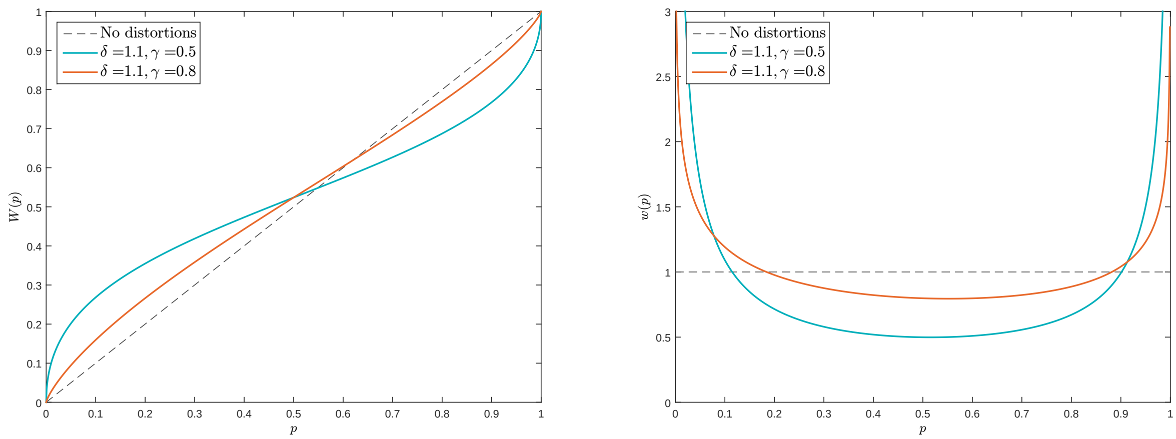
2.1 Modeling probability weighting

The main interest in this section is to represent banks' attitudes to risk and later examine their ability to explain asset prices of large banks that were recapitalized under the Capital Purchase Program in 2008. For this reason, we briefly revise the psychology of attention in Tversky and Kahneman (1992) where the decision-maker evaluates lotteries by overweighting the most salient states.

Most models of decision making under risk suppose that investors assess risk according to the expected utility theory, in that they treat payoff probabilities linearly. A well-known exception to this rule is the prospect theory of Tversky and Kahneman (1992), which differs from the expected utility framework in two aspects. These disparities can be understood in terms of how people transform values and probabilities. First, agents perceive market or economic outcomes and payoffs as gains and losses relative to the reference point or status quo. In doing so, agents exhibit loss aversion: higher sensitivity towards negative in comparison to positive payoffs. Intuitively, agents frame events as chances for success or failure and dislike failing more than they like succeeding.

Moreover, if the possibility for success or failure is low, people overweight it, and vice versa, they underweight a high chance of succeeding and failing. Therefore, in addition to framing, individuals' behavior is governed by distorting objective probabilities of outcomes or lotteries. Small probabilities and rare events are overweighted, and high probability events underweighted. The risk spectrum and the probability weighting function capture this violation of linearity in expectations and convey subjective probabilities assigned to events—both approximate the agent's capacity to pay attention to multiple outcomes, and his or her risk attitudes.

Figure 1(a) and (b) illustrate departures from expected utility and linear probability weighting. The dashed 45-degree line corresponds to the objective probability of the expected utility theory. If the weighting function is above the dashed line, investors overweight the likelihood of those states. Conversely, investors underweight objective probabilities if decision weights are below this line.



(a) Probability weighting function

(b) Risk spectrum

Figure 1: Probability weighting functions and risk spectrum in prospect theory. *Notes*: The left panel plots the probability weighting function proposed by Gonzalez and Wu (1999), $W(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$ for various parameter values of δ and γ. The right panel plots the associated risk spectrum $w(p) = W'(p)$.

Spectral risk measures are defined as the weighted average of quantiles of a profit-loss probability distribution

$$M_w(X) = \int_0^1 w(p)F^{-1}(p)dp \quad (1)$$

where $F^{-1}(\cdot)$ is a quantile function of a random variable X which defines market losses.[2] The function $w(p)$ is called the risk spectrum and reflects the degree of subjective risk aversion or seeking. It is related to the probability weighting function or decision weights $W(p)$ in Tversky and Kahneman (1992) such that $W'(p) = w(p)$ holds. In effect, spectral risk measures

[2]Quantile at level p is a an inverse of cumulative distribution function of a random variable X, that is $F^{-1}(p) = \inf\{x \;\; : F(x) \equiv Prob\,[X \leq x] \geq p\}$.

are the certainty equivalent or *expected prospect value* that agents assign to risky gamble with continuous payoffs.

We specify the probability weighting function in two ways. First, we hypothesize that banks' risk attitudes are consistent with prospect theory and test this assumption. To do so, we use Gonzalez and Wu (1999)'s probability distribution in Figure 1(a), which overweights the risk in the tails as evidenced by its risk spectrum (Figure 1(b)).In technical terms, this type of distortions are represented by two functions

$$w(p) = \frac{\delta\gamma(p(1-p))^{\gamma-1}}{(\delta p^{\gamma} + (1-p)^{\gamma})^2} \tag{2}$$

$$W(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} \tag{3}$$

Alternatively, we choose third degree polynomial to represent probability weighting function

$$W(p) = \frac{a}{3}p^3 + \frac{b}{2}p^2 + cp, \tag{4}$$

and quadratic risk spectrum

$$w(p) = ap^2 + bp^2 + c. \tag{5}$$

Figure 6(a) and (b) in Appendix B depicts these functions for various values of parameters a, b and c. Since $W(1) = 1$, it implies that $\frac{a}{3} + \frac{b}{2} + c = 1$ holds. Therefore, only two parameters a and b need to be estimated, while $c = 1 - \frac{a}{3} - \frac{b}{2}$.

Intuitively, the curvature of the probability weighting function reflects the tendency of the individual to pay comparatively more attention to less probable outcomes. The possibility effect (overweighting of small probabilities) favors risk seeking for gains and risk aversion for losses. In contrast, the certainty effect (underweighting large probabilities) encourages risk seeking in the domain of losses and risk aversion for gains.

Since the formulation of original prospect theory, there has been further progress in establishing psychological foundations for the weighting function. Gonzalez and Wu (1999) differentiate between the degree of curvature and elevation of the weighting function in governing investment behavior. The curvature or *discriminability*, characterizes sensitivity to changes in probability.[3] For example, investors with linear weighting function exhibit constant sensitivity to changes in probability. In contrast, those with a step function are extremely sensitive to changes around 0 (impossibility) and 1 (certainty) and insensitive in the intermediate domain. In prospect theory, discriminability is evident in Figure 1(a) as probability distortions are highest around two reference points of 0 and 1. The second feature, *attractiveness*, instills the strength of overweighting. In gains domain, the first investor finds gambling and chance more attractive if his weighting function is more elevated, i.e., $W_1(p) \geq W_2(p)$. In the loss domain, a higher elevation is associated with higher risk aversion and preferences for insurance

[3]In technical terms, if the first investor with weighting function $W_1(p)$ distinguishes probabilities to higher degree than the second investor with weighting function $W_2(p)$ within the interval $[p_1, p_2]$, then $W_1(p+\epsilon) - W_1(p) \geq W_2(p+\epsilon) - W_2(p)$.

against rare adverse events.

In the following section, we derive the asset pricing equation from which we estimate the probability weighting function.

2.2 Asset pricing under probability weighting

The model is a simplified version of Brunnermeier and Sannikov (2014) with the financial sector operating under the expected loss constraint. There is a single consumption good and a single factor of production (capital). There is one type of agent, risk-averse banks with the discount rate ρ. The utility of bankers is given by

$$E\left[\int_0^\infty e^{-\rho t}\log c_t dt\right]. \tag{6}$$

Banks produce final good from capital, with linear production function

$$y_t = Ak_t, \tag{7}$$

where A is a technology parameter. Let q_t be the price of capital. Capital supply is exogenous, and evolves over time according to Brownian motion

$$\frac{dk_t}{k_t} = \sigma dW_t, \tag{8}$$

The term dW_t is called *capital quality* shock, and it captures changes in expectation about future productivity of capital. In principle, banks can finance any process for k_t by taking debt at exogenous risk-free rate r_t, such that their net worth evolves as

$$dn_t = Ak_t d_t + d(q_t k_t) - r_t(q_t k_t - n_t)dt - c_t dt. \tag{9}$$

The first two terms are income from production and capital gains or losses, that is change in asset value. The second two terms are debt repayments and consumption. The price of capital follows diffusion process

$$\frac{dq_t}{q_t} = \mu_t^q dt + \sigma^q dW_t. \tag{10}$$

Using Ito's product rule and the evolution of capital and the price of capital we have get evolution of capital gains rate

$$\frac{d(q_t k_t)}{q_t k_t} = (\mu_t^q + \sigma\sigma_t^q)dt + (\sigma + \sigma_t^q)dW_t. \tag{11}$$

2.3 Banks optimization problem : expected loss constraint

Now let us consider how spectral risk measures enter the banks' optimization problem. Recall that these risk measures are applied to a loss process here defined as follows. Let $V_t \equiv q_t k_t$

denote the value of capital at time t so that $V_{t+\tau}$ would be the future value of capital at time $t+\tau$ if the capital exposure between time t and time $t+\tau$ were kept unchanged, meaning that experts would not change their capital demand. We define loss between the trading period t and $t+\tau$

$$Loss(t, t+\tau) \equiv V_{t+\tau} - V_t. \tag{12}$$

The interpretation of this is that bank assets are marked to market, so marked-to-market gains and losses are captured by the change of the value of capital $d(q_t k_t)$. We assume that banker's borrowing is restricted by risk-based capital constraint. To compute these measures we first need the definition of the quantile of loss distribution or more commonly known as Value at Risk in the financial industry. Value at Risk is the maximum loss on assets one can likely lose over a period at a specific confidence level p, that is

$$P(Loss(t, t+\tau) \leq VaR_p^{t,t+\tau}) = p.$$

$VaR_p^{t,t+\tau}$ is the loss over the next period of length τ which would be exceeded only with a probability p if the current portfolio were kept unchanged. In Appendix we present the proof for the following propositions.

Proposition 1.

$$F^{-1}(p) = VaR_p^{t,t+\tau} = q_t k_t (1 - \mathrm{e}^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau})}),$$

where $\Phi^{-1}(\cdot)$ is the inverse of the cumulative distribution function of the standard normal distribution.

Proposition 2. *Distortion risk measures for Kahneman-Tversky's and cubic probability weighting functions are*

$$\begin{aligned}
RM_{KT} &= q_t k_t \int_0^1 g_{KT}(p) F^{-1}(p) dp \\
&= q_t k_t \int_0^1 \frac{\delta\gamma(p(1-p))^{\gamma-1}}{(\delta p^\gamma + (1-p)^\gamma)^2} (1 - \mathrm{e}^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}}) dp \\
&= q_t k_t \left(1 - \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau} \frac{\delta\gamma(\Phi(\sigma+\sigma^q)(1-\Phi(\sigma+\sigma^q)))^{\gamma-1}}{(\delta\Phi(\sigma+\sigma^q)^\gamma + (1-\Phi(\sigma+\sigma^q))^\gamma)^2}\right) = q_t k_t M_{KT},
\end{aligned}$$

and

$$\begin{aligned}
RM_{CU} &= q_t k_t \int_0^1 g_{CU}(p) F^{-1}(p) dp \\
&= q_t k_t \int_0^1 (ap^2 + bp^2 + c)(1 - \mathrm{e}^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}}) dp \\
&= q_t k_t \left(1 - \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau} \left(c + (b+a)\Phi(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}}) - 2aT(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}}, \frac{1}{\sqrt{3}})\right)\right) \\
&= q_t k_t M_{CU}
\end{aligned}$$

, where $T(\cdot,\cdot)$ is Owen's T function.

Note that M_{KT} and M_{CU} represent subjective assessment of downside market risk. Therefore, we impose the constraint on banks that their net worth at any time t is sufficient to cover future subjective risk at time t over the horizon of length τ,

$$q_t k_t M_t \leq n_t \tag{13}$$

Banks choose k_t and c_t to maximize expected utility (6) subject to net worth evolution (9) and the expected loss constraint (13). The constraint itself may be imposed by banks' investors, regulatory authority, or voluntarily by banks themselves. Alternatively, the constraint reflects collective perception and an assessment of market losses by three agents. Hereafter, we refer to subjective expected losses as losses perceived by banks.

The optimization problem combines a standard expected utility consumption-portfolio model, with a behavioral one that applies prospect theory to how banks evaluate risk. This approach is consistent with the one proposed by Kőszegi and Rabin (2006) and Barberis et al. (2016) who argue that agents derive utility both from wealth levels and realized gains-losses, and as such, formulations where agents' decisions are determined solely by prospect theory should be avoided.

Proposition 3. *The optimization problem by solving Hamilton-Jacobi-Bellman equation leads to banks asset pricing equation*

$$\frac{A}{q_t} + \mu_t^q + \sigma\sigma_t^q - r_t = \frac{1}{M_t}(\sigma + \sigma_t^q)^2 + \xi q_t M_t, \tag{14}$$

where ξ is a Lagrange multiplier on the expected loss constraint (13).

The proof is in Appendix A. The Lagrange multiplier captures banks' risk attitudes, so the equity premium they earn on capital equals the risk premium plus *salience loss* premium. Positive salience loss premium implies risk aversion in losses, and banks demand additional payment for being exposed to expected market losses. Conversely, with negative salience loss premium, banks are risk-seeking in market losses. Therefore, ξ captures the curvature of the value function in the domain of losses.

3 Data and methodology

3.1 Capital Purchase Program Background

With the onset of the 2008 market downturn, the Troubled Asset Relief Program (TARP) was established by the Treasury to stabilize the US financial system. The Capital Purchase Program (CPP), under which liquidity constrained financial institutions received capital injections from Treasury, was the first and largest TARP program. The capital was provided to 707 financial institutions by purchasing preferred stocks. The program started with October-December 2008 recapitalizations, while the final investments under the CPP were made in December 2009. CPP injected up to 250 billion in banks. 81 % of the total CPP funds were distributed to 17 out of 19 banks with total assets above 100 billion. The remaining funds were allocated to 690 out of 7,891 banks with assets of less than 100 billion. Through other programs, TARP either provided capital injections (Targeted Investment Program and Systematically Significant Failing Institutions Program) or guaranteeing and removing troubled securities from bank balance sheets(Asset Guarantee Program and Public-Private Investment Program).

At the beginning of the CPP, the government described its goals for the program. Treasury said that the program's primary purpose was to stabilize the financial system, while its secondary objective was to improve credit availability. Treasury further explained that it included banks of all sizes in order to increase credit availability to the communities served by disparate banks. Table 1 reposts the large banks included in the estimation analysis in the following sections. The minimum investment in our sample is 214 million dollars to Umpqua Holdings Corporation, the maximum of 25 billion dollars was distributed to both Citigroup Inc and Wells Fargo & Company, amounting to the total investment of 96.6 billion dollars to 39 banks.

3.2 Data

The sample consists of daily equity data of 39 banks covering the period between January 2nd, 2007, and December 31st, 2010. We estimate coefficients of probability weighting function during four periods: before the Capital Purchase Program (January 2nd, 2007 - June 30th, 2008), during the CPP (September 2nd - December 26th, 2008), before-during the CPP (January 2nd, 2007 - December 26th, 2008) and after the CPP (January 2nd, 2010 - December 31st, 2010). Table 2 contains the data sources and empirical counterparts related to the GMM estimation. Summary statistics in periods before, during and after the CPP for core variables and instruments are provided in Table 3.

We use five Fama-French risk factors as instruments Z_t for restricted GMM. In particular, in baseline specification, we use five Fama-French factors, namely market (MktRF), size (small-minus-big, SMB), value (high-minus-low, HML), profitability (robust-minus-weak, RMW), and investment (conservative-minus-aggressive, CMA) factor. We also use book-to-market factors (BM0, Lo30, and Med40) and momentum factor (MoM) interchangeably instead of MktRF. The idea is that the literature on equity premium offers two different views on the underlying economic drivers of the equity premium or excess return. In institutional or agency view, the risk-adjusted return is driven by leverage constraints, and risk should be measured using systematic risk (Frazzini and Pedersen (2014)). In the behavioral view, the excess return reflects behavioral effects, and risk should be measured using idiosyncratic risk(Barberis and Huang (2008)). Given that the return of all factors except market and momentum is consistent with the theory of leverage constraint, the idea is that probability distortions capture behavioral factors separate from leverage factors.

3.3 Econometric procedure : estimation of the probability weighting function

The fundamental question we ask is how big banks exposed to insolvency risk perceive market losses? To put differently, how biggest banks tend to distort probabilities?

Table 1: List of CPP recipients

Institution	Amount invested	Amount returned
Citigroup Inc.	25 000	32 839
Wells Fargo & Company	25 000	27 281
The PNC Financial Services Group Inc.	7 579	8 320
U.S. Bancorp	6 599	6 933
Capital One Financial Corporation	3 555	3 806
Regions Financial Corporation	3 500	4 138
SunTrust Banks, Inc.	3 500	5 448
Fifth Third Bancorp	3 408	4 043
Key Corp	2 500	2 867
Comerica Inc.	2 250	2 582
State Street Corporation	2 000	2 123
Marshall & Ilsley Corporation	1 715	1 944
Northern Trust Corporation	1 576	1 709
Zions Bancorporation	1 400	1 661
Synovus Financial Corp.	967	1 191
Popular, Inc.	935	1 220
First Horizon National Corporation	866	1 037
M&T Bank Corporation	600	718
First BanCorp	424	237
Webster Financial Corporation	400	457
City National Corporation	400	442
Fulton Financial Corporation	376	416
TCF Financial Corporation	361	378
South Financial Group, Inc.	347	146
Wilmington Trust Corporation	330	369
East West Bancorp	306	352
Sterling Financial Corporation	303	121
Susquehanna Bancshares, Inc	300	328
Citizens Republic Bancorp, Inc.	300	381
Whitney Holding Corporation	300	343
Valley National Bancorp	300	318
Flagstar Bancorp, Inc.	266	277
Cathay General Bancorp	258	329
Wintrust Financial Corporation	250	300
Private Bancorp, Inc.	243	290
SVB Financial Group	235	253
International Bancshares Corporation	216	261
Trustmark Corporation	215	236
Umpqua Holdings Corp.	214	7

Source : U.S. Department of the Treasury. Amounts in millions of U.S. Dollars.

Table 2: BIGGEST BANKS DATA

Variable	Empirical counterpart	Source
Core Variables		
$\frac{A}{p_t} + \mu^q$	Holding period returns with dividends	CRSP
σ	VIX (The CBOE Volatility Index)	OptionMetrics
r_t	Treasury bill rate	Fama-French Data Library
σ_t^q	Historical volatility	OptionMetrics
q_t	Equity price (Bid/Ask)	CRSP
Instruments		
MktRF	Excess return on the market, value-weight return of all CRSP firms incorporated in the US minus the one-month Treasury bill rate (from Ibbotson Associates)	Fama-French Data Library
SMB	Small Minus Big is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios	Fama-French Data Library
HML	High Minus Low is the average return on the two value portfolios minus the average return on the two growth portfolios	Fama-French Data Library
RMW	Robust Minus Weak is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios	Fama-French Data Library
CMA	Conservative Minus Aggressive is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios	Fama-French Data Library
MoM	Average return on the two high prior return portfolios minus the average return on the two low prior return portfolios	Fama-French Data Library
BM0	Average return on portfolios formed on BE/ME (Book equity/Market equity), firms with negative book equity	Fama-French Data Library
Lo30	Average return on portfolios formed on BE/ME (Book equity/Market equity), bottom 30% firms	Fama-French Data Library
Med40	Average return on portfolios formed on BE/ME (Book equity/Market equity), middle 40% firms	Fama-French Data Library

In a nutshell, to answer this question, we consider four periods, before the Capital Purchase Program (January 2nd 2007 - June 30th 2008), during CPP (September 2nd - December 26th 2008), before-during CPP (January 2nd 2007 - December 26th 2008) and after CPP (January 2nd 2010 - December 31st, 2010).

In technical terms, we estimate coefficients δ and γ of the probability weighting function

Table 3: Data Summary : Core Variables

	before CPP	during CPP	after CPP
Return			
Mean (SD)	-0.00171 (0.0258)	-0.000598 (0.0814)	0.00110 (0.0321)
Median [Min, Max]	-0.00148 [-0.298, 0.259]	-0.00287 [-0.436, 0.578]	0.000366 [-0.523, 0.667]
Volatility			
Mean (SD)	0.344 (0.227)	1.22 (0.607)	0.429(0.509)
Median [Min, Max]	0.294 [0.0240, 2.22]	1.08 [0.158, 4.58]	0.367 [0.0388, 31.7]
Price			
Mean (SD)	39.0 (23.1)	23.9 (18.1)	21.4 (18.6)
Median [Min, Max]	34.1 [2.74, 125]	18.0 [0.500, 95.5]	14.8 [0.235, 94.5]
Volatility S&P 500			
Mean (SD)	0.167 (0.0750)	0.650 (0.227)	0.163 (0.0815)
Median [Min, Max]	0.162 [0.0368, 0.417]	0.696 [0.179, 1.09]	0.152 [0.0266, 0.442]
Treasury Yield			
Mean (SD)	0.0147 (0.00506)	0.00302 (0.00271)	0.000756 (0.000430)
Median [Min, Max]	0.0160 [0.00700, 0.0220]	0.00400 [0, 0.00700]	0.00100 [0, 0.00100]
Observations	12,188	3,013	9,249

and Lagrange multiplier ξ in the asset pricing equation (15) by the general method of moments

$$E\left[\left(\frac{A}{q_t} + \mu_t^q + \sigma\sigma_t^q - r_t - \frac{1}{M_t}(\sigma + \sigma_t^q)^2 - \xi q_t M_t\right) Z_t\right] = 0 \tag{15}$$

where

$$M_t = 1 - \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau} \frac{\delta\gamma(\Phi(\sigma+\sigma^q)(1-\Phi(\sigma+\sigma^q)))^{\gamma-1}}{(\delta\Phi(\sigma+\sigma^q)^\gamma + (1-\Phi(\sigma+\sigma^q))^\gamma)^2} \tag{16}$$

are subjective value of market losses using Gonzalez and Wu (1999)'s probability weighting function. As a robustness test, Appendix B, reports results when we estimate coefficients a, b, c and ξ from (15) and subjective expected losses under cubic distortions

$$M_t = 1 - \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau} \left(c + (b+a)\Phi(\frac{(\sigma+\sigma^q)}{\sqrt{2}}) - 2aT(\frac{(\sigma+\sigma^q)}{\sqrt{2}}, \frac{1}{\sqrt{3}})\right). \tag{17}$$

3.4 Estimating probability weighting function

In this section, we test types of probability distortions consistent with prospect theory. The prospect theory violates the one-to-one relationship between risk attitudes and the concavity or convexity of value/utility function that holds under expected utility. In prospect theory framework, risk attitudes are jointly determined by curvature of value function and subjective probability weighting. The tightness of expected loss constraint can be thought of as a proxy for the curvature of the value function in domain of losses in Tversky and Kahneman (1992) formulation. As previously mentioned, the probability weighting function constitutes "the local thinking" and captures the strength of the decision maker's focus on salient states. In this way, it proxies for the agent's ability to pay attention to multiple events or outcomes.

Table 4 to 7 present the baseline GMM estimation of parameters of Kahneman-Tversky's probability distortion for various combinations of 5 Fama-French factors as instruments. Specifically, notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Figure 2(a) and 2(c) summarize the results of the baseline model and depict probability weighting functions estimated with all five Fama-French factors as instruments during four periods: before CPP, during CPP, before and during CPP, and after CPP. The main question we ask is, do banks consistently distort probabilities, or do distortions vary across periods? To address this focal question, we report banks' attractiveness to gambling δ and sensitivity to probabilities γ.

Before the CPP recapitalization, point estimates for δ and γ are 0.49 and 0.85 and significant, while estimates for ξ range from 0.12 to 0.15 and are insignificant. δ below 1 points to sizable underweighting of tail market losses and optimistic risk attitudes, the hypothesis which we do not reject (p-value(λ^2)=0.000 for hypothesis $\delta = 1$). This optimism is strengthened by reduced responsiveness to probability changes (p-value(λ^2)=0.000 for hypothesis $\gamma = 1$). Regarding the justification of government intervention, positive estimates of ξ in Table 4 might hint that banks were encountering difficulties in the management of their liquidity. However, we cannot reject the hypothesis that large banks were sufficiently capitalized before the government intervention(p-value(λ^2)=0.6841 for hypothesis $\xi = 0$).

During the government intervention, banks overweighted tail market losses as Figure 2(a) and estimate for $\delta = 2.2$ in Table 5 suggest. For losses, elevated probability weighting function above the 45-degree line implies that banks were pessimistic, and overweight probabilities relative to objective probabilities. We also obtain slightly higher sensitivity as $\gamma = 0.91$ is closer to 1. In column (7) of Table 5, we report estimated coefficients when defining the CPP period from the date of the first CPP recipient until the last date of bank recapitalization in the sample(October 26th, 2008 until January 30th, 2009). Elevation and curvature remain almost unchanged as $\delta = 2.26$ and $\gamma = 0.91$.

Isolating periods before and during the CPP, large banks substituted optimism for pessimism. However, when estimating probability weighting functions jointly before and during the CPP, an inverse-S shape of prospect theory of Tversky et al. (1990) arises. As such, banks' behavior is most responsive around two reference points of 0 (impossibility) and 1 (certainty) and almost unresponsive to the middle region, as evidenced in Figure 2 (d). What surprises us most, however, is that if we consider banks' average preferences, these reveal theoretically meaningful values found in laboratory settings. Most empirical findings regarding probability weighting suggest that probabilities in the range $(0.2, 0.8)$ are treated close to linear. Now, estimates of δ and γ are 1.12 and 0.8 (Table 6, column (6)) and close to those found in litera-

Table 4: GMM estimation of Kahneman-Tversky's probability weighting function before the CPP

This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the five Fama-French factors : market (MktRF),size(SMB), value(HML),profitability (RMW) and investment (CMA). Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample period is from January 2nd, 2007, through June 30th, 2008.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	0.48***	0.49***	0.48***	0.49***	0.49***	0.49***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
γ	0.85***	0.85***	0.85***	0.85***	0.85***	0.85***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ξ	0.13	0.15	−0.15	0.15	0.12	0.12
	(0.30)	(0.32)	(1.24)	(0.34)	(0.29)	(0.29)
MktRF		Y	Y	Y	Y	Y
SMB	Y		Y	Y	Y	Y
HML	Y	Y		Y	Y	Y
RMW	Y	Y	Y		Y	Y
CMA	Y	Y	Y	Y		Y
J-test p-value	0.89	0.95	0.99	0.91	0.84	0.98
Observations	12,188	12,188	12,188	12,188	12,188	12,188

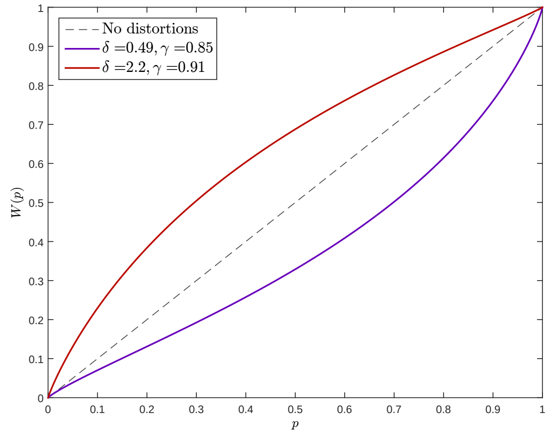
Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: GMM estimation of Kahneman-Tversky's probability weighting function during the CPP

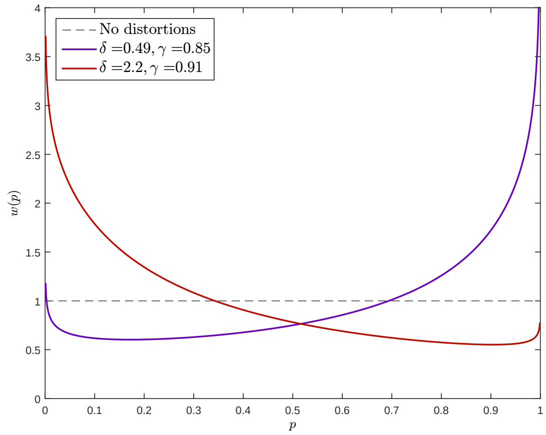
This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the five Fama-French factors : market (MktRF), size (SMB), value (HML), profitability (RMW), and investment (CMA). Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample period is from September 2nd, 2008, through December 26th, 2008 in columns (1)-(6) and October 26th, 2008, through January 30th, 2009 in column (7).

	Asset Pricing Equation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ	2.55***	2.04***	2.46***	2.20***	2.08***	2.20***	2.26***
	(0.02)	(0.05)	(0.02)	(0.03)	(0.01)	(0.00)	(0.01)
γ	0.99***	0.89***	0.78***	0.87***	0.84***	0.91***	0.91***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
ξ	0.09	0.14	−0.03	0.06	−0.04	0.07	0.04
	(1.78)	(0.44)	(0.07)	(0.46)	(0.06)	(0.32)	(0.18)
MktRF		Y	Y	Y	Y	Y	Y
SMB	Y		Y	Y	Y	Y	Y
HML	Y	Y		Y	Y	Y	Y
RMW	Y	Y	Y		Y	Y	Y
CMA	Y	Y	Y	Y		Y	Y
J-test p-value	0.95	0.99	0.93	0.93	0.86	0.97	0.93
Observations	3,013	3,013	3,013	3,013	3,013	3,013	2,545

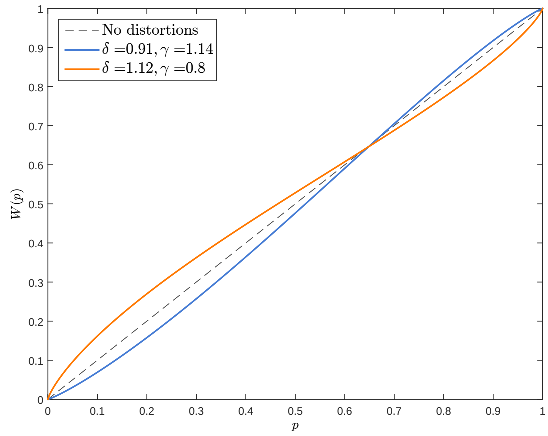
Note: *p<0.1; **p<0.05; ***p<0.01



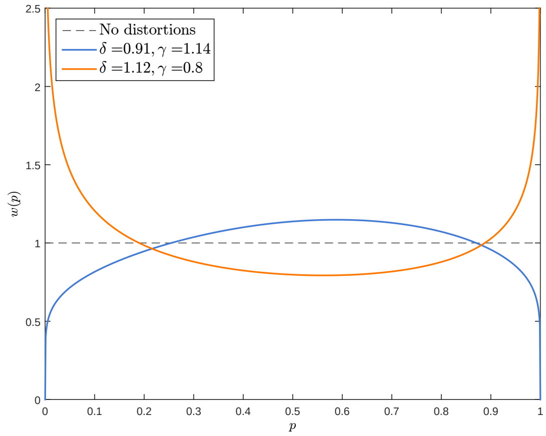
(a) Probability weighting function KT : before and during CPP



(b) Risk spectrum KT: before and during CPP



(c) Probability weighting function KT : before-during and after CPP



(d) Risk spectrum KT: before-during and after CPP

Figure 2: Estimated probability weighting functions and risk spectrum of big banks. *Notes*: Left panels plot the probability weighting function of Gonzalez and Wu (1999), $W(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$, for estimated parameter values of δ and γ during four periods : before, during, before-during and after the Capital Purchase Program. The right panels plot the associated risk spectrum $w(p) = W'(p)$.

ture that applies prospect theory in laboratory settings. Closest to our results, Etchart-Vincent (2004) find $\delta = 1.1$ and $\gamma = 0.84$ in domain of losses. Abdellaoui et al. (2005) reports more pessimistic responses ($\delta = 1.35$) and similar sensitivity ($\gamma = 0.84$). Fehr-Duda et al. (2006) explore gender-specific probability weighting in abstract and context environments in which lotteries are framed as an investment and insurance decisions. In comparison to our results, participants discriminate probabilities less than financial institutions ($\gamma = 0.57$ for men and $\gamma = 0.47$ for women), and exhibit similar degree of pessimism ($\delta = 1.14$ for men and $\delta = 1.06$ for women in contextual setting, and $\delta = 1.1$ for men and $\delta = 1.10$ for women in abstract gamble formulations). In financial market environment, Kliger and Levy (2009) find that considerable nonlinear weighting probabilities is supported by call options data ($\delta = 0.4, \gamma = 0.33$). To ensure the robustness of an inverse S-shaped distortions, we parametrize and estimate cubic probability weighting function in Appendix B. We find that the results are not sensitive to the specification of the weighting function.

Table 6: GMM estimation of Kahneman-Tversky's probability weighting function before and during the CPP

This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the five Fama-French factors : market (MktRF), size (SMB), value (HML),profitability (RMW), and investment (CMA). Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample period is from January 2nd, 2007, through December 26th, 2008.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	1.13***	1.17***	1.10***	1.10***	1.24***	1.12***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
γ	0.85***	0.94***	0.87***	0.74***	0.75***	0.80***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ξ	0.01	−0.06	0.04	0.02	−0.02	−0.03
	(0.08)	(0.30)	(0.13)	(0.03)	(0.09)	(0.05)
MktRF		Y	Y	Y	Y	Y
SMB	Y		Y	Y	Y	Y
HML	Y	Y		Y	Y	Y
RMW	Y	Y	Y		Y	Y
CMA	Y	Y	Y	Y		Y
J-test p-value	1	0.97	0.96	0.92	0.97	0.93
Observations	16,670	16,670	16,670	16,670	16,670	16,670

*p<0.1; **p<0.05; ***p<0.01

After the CPP, the probability weighting function is S-shaped, as shown in Figure 2(c), implying an optimistic psychological response toward the probability of obtaining the worst possible outcome. Table 7 suggest that $\delta = 0.91$ and $\gamma = 1.14$ after recapitalization. Therefore, banks are not attracted to gambling and started paying substantial attention to changes in loss probabilities. Most studies that report a parametric estimate of the Gonzalez and Wu (1999) weighting function find evidence of an inverse-S shaped weighting function. However, some studies do find a sensitivity or discriminability parameter larger than one (Goeree et al. (2002); Van de Kuilen and Wakker (2011)).

In summary, we find a fourfold probability weighting pattern: convex(underweighting) before the CPP, concave(overweighting) during the CPP, inverted S-shaped before-during the CPP, and S-shaped after the CPP. This result is robust to the inclusion of book-to-market or momentum factors as instruments instead of the market factor MktRF. Table 8 summarizes results or GMM estimation with BM0(book-to-market below zero), Lo30 (lowest 30%) and Med40 (middle 40 %) factors. Similarly, Table 9 substitutes momentum factor MoM instead of MktRF. Figure 3 plots resulting estimated probability distortions, which are quantitatively similar to the results of the baseline GMM.

Interestingly, once GMM is estimated with Lo30, we find the support that banks were constrained and risk-averse in losses before-during the crisis. In this case, $\xi = 0.13$ and we do reject the hypothesis of unconstrained banks at 5% level (p-value(λ^2) = 0.03662 for hypothesis $\xi = 0$). Banks shift to risk-seeking after they have been recapitalized as $\xi = -0.59$ with Med40 instrument (p-value(λ^2) = 0.08098 for hypothesis $\xi = 0$). In this regard, book-to-market equity seems to be a stronger predictor of big banks' risk attitudes than the overall market return.

Table 7: GMM estimation of Kahneman-Tversky's probability weighting function after the CPP

This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the five Fama-French factors : market (MktRF),size (SMB), value (HML),profitability (RMW), and investment (CMA). Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample period is from January 2nd, 2010, through December 31st, 2010.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	0.87***	0.84***	0.90***	0.70***	0.83***	0.91***
	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
γ	1.37***	1.16***	1.15***	1.26***	1.11***	1.14***
	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
ξ	−0.31	−0.52	−0.20	−0.05	0.23	0.13
	(0.29)	(0.33)	(0.22)	(0.10)	(0.18)	(0.23)
MktRF		Y	Y	Y	Y	Y
SMB	Y		Y	Y	Y	Y
HML	Y	Y		Y	Y	Y
RMW	Y	Y	Y		Y	Y
CMA	Y	Y	Y	Y		Y
J-test p-value	0.91	0.94	0.87	0.99	1	0.96
Observations	9,249	9,249	9,249	9,249	9,249	9,249

Note: *p<0.1; **p<0.05; ***p<0.01

3.5 Discussion

As demonstrated in Figure 2 and Table 4 to 8, we do not find support for the consistency of probability weighting function. Instead, the fourfold pattern emerges, we obtain concave, convex, concave-convex, and convex-concave weighting functions during four periods. The loss probability weighting function is a bad-news probability transformation; i.e., it maps the de-

Table 8: GMM estimation of Kahneman-Tversky's probability weighting function with Book-to-Market instrument

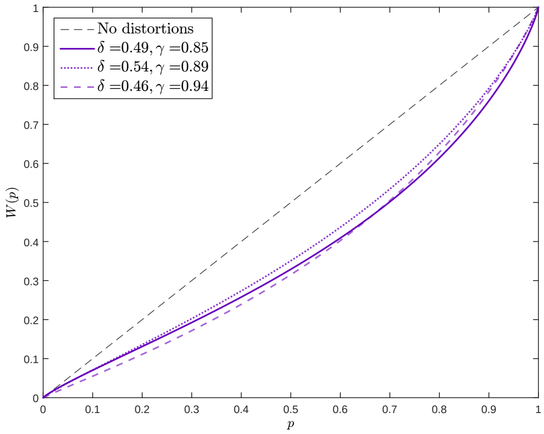
This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the seven Fama-French factors : size (SMB), value (HML),profitability (RMW), investment (CMA) and three book-to-market factors, BM0, Lo30 and Med40. Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample periods are before the CPP (January 2nd, 2007, through June 30th, 2008), during the CPP (September 2nd, 2008, through December 26th, 2008), before-during the CPP (January 2nd, 2007, through December 26th, 2008) and after the CPP (January 2nd, 2010, through December 31st, 2010).

	Asset Pricing Equation			
	before CPP	before-during CPP	during CPP	after CPP
δ	0.54***	1.04***	2.37***	0.84***
	(0.00)	(0.00)	(0.01)	(0.00)
γ	0.89***	0.92***	0.80***	1.16***
	(0.00)	(0.00)	(0.00)	(0.00)
ξ	-0.07	0.13**	0.00	-0.59^{*}
	(0.40)	(0.06)	(0.08)	(0.34)
SMB	Y	Y	Y	Y
HML	Y	Y	Y	Y
RMW	Y	Y	Y	Y
CMA	Y	Y	Y	Y
BM0			Y	
Lo30	Y	Y		
Med40				Y
J-test p-value	0.97	0.95	0.99	0.97
Observations	12,188	16,670	3,013	9,249
Note:			*p<0.1; **p<0.05; ***p<0.01	

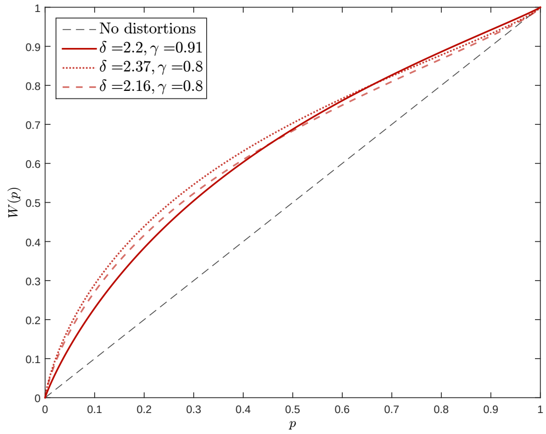
Table 9: GMM estimation of Kahneman-Tversky's probability weighting function with momentum instrument

This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the five Fama-French factors : size (SMB), value (HML),profitability (RMW), investment (CMA) and momentum (MoM). Notation Y indicates if an instrument is used in estimation, while the p-value of Hansen J statistics is provided as guidance for model selection. Standard errors are reported in parentheses. The sample periods are before the CPP (January 2nd, 2007, through June 30th, 2008), during the CPP (September 2nd, 2008, through December 26th, 2008), before-during the CPP (January 2nd, 2007, through December 26th, 2008) and after the CPP (January 2nd, 2010, through December 31st, 2010).

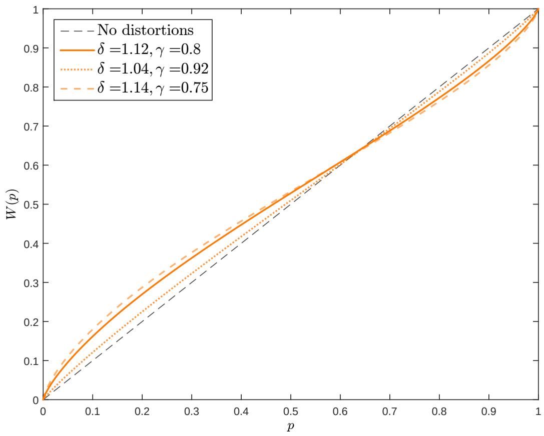
	Asset Pricing Equation			
	before CPP	before-during CPP	during CPP	after CPP
δ	0.459***	1.138***	2.156***	0.930***
	(0.002)	(0.001)	(0.013)	(0.002)
γ	0.944***	0.749***	0.803***	1.138***
	(0.001)	(0.001)	(0.005)	(0.001)
ξ	−0.076	−0.010	0.141	−0.058
	(0.065)	(0.013)	(0.117)	(0.554)
SMB	Y	Y	Y	Y
HML	Y	Y	Y	Y
RMW	Y	Y	Y	Y
CMA	Y	Y	Y	Y
MoM	Y	Y	Y	Y
J-test p-value	0.924	0.95	0.981	0.923
Observations	12,188	16,670	3,013	9,249
Note:				*p<0.1; **p<0.05; ***p<0.01



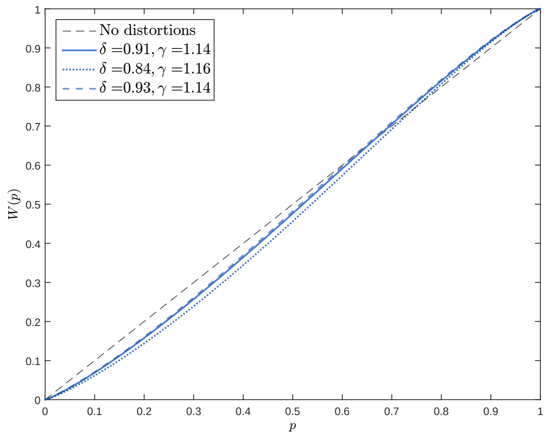
(a) Before the CPP



(b) During the CPP



(c) Before and during the CPP



(d) After the CPP

Figure 3: Estimated probability weighting functions with book-to-market and momentum instruments. *Notes*: All lines plot the probability weighting function of Gonzalez and Wu (1999), $W(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$, for estimated parameter values of δ and γ during four periods : before, during, before-during and after the Capital Purchase Program. The parameters from GMM estimation are obtained using four Fama-French factors as instruments (SMB, HML, RMW, and CMA) and MktRF (solid line), book-to-market (BM0,Lo30,or Med40) (dotted line) or MoM (dashed line) factors as the fifth instrument.

cision weight of the worst outcome. Before the Great Recession, the largest banks tended to underweight the probability of tail losses, which generates the convex shape. During market turmoil and amid the CPP recapitalization, banks overweight the likelihood of the worst possible scenario. Merging the crisis and pre-crisis period generates an inverted S-curve, while the weighting function is S-shaped following the CPP. The second result is that banks are risk-averse in losses before and during government intervention, and risk-seeking afterward.

That said, several questions arise immediately. What explains the differences in how banks distort probabilities in favorable and unfavorable situations? Is there one probability weighting function? What accounts for the shift in risk attitudes?

The assumption we make in our model is that banks are expected utility optimizers subject to expected loss constraint, and losses are evaluated according to prospect theory. As a rational decision theory of choice under risk and uncertainty, expected utility postulates that people exhibit consistent risk aversion across any decision concerning uncertain outcomes. The tendency to choose a sure payoff over uncertain gamble arises because of the diminishing marginal utility of wealth as the utility function is concave in the domain of gains and losses. However, our results acknowledged that the largest banks' behaviors reveal inconsistent risk attitudes across different circumstances. As such, EUT cannot explain simultaneous gambling and insuring preferences of large financial institutions: banks fear tail losses at one time and hope to avoid them at other times. As some authors have argued, EUT is frequently violated because it neglects hopes and fears associated with risky outcomes.

Reflection effect reveals that people have contradicting risk preferences for uncertain choices, depending on whether the outcome is likely or unlikely, or framed as gain or loss. Prospect theory of Tversky and Kahneman (1992) predicts decision-makers seek risk in losses of high probability and avoid risk when losses are unlikely. The certainty effect (underweighting of large probabilities) generates risk seeking, while possibility effect (overweighting small probabilities) elicits risk aversion. Thus, banks shift to risk aversion when the possibility effect reflects into certainty effect; that is when a mere chance of tail loss becomes almost unavoidable. According to prospect theory, when contemplating the choice between sure loss and a gamble with a high probability of even more detrimental outcomes, diminishing sensitivity makes sure loss more aversive. At the same time, the certainty effect reduces the banks' aversiveness to take the gamble. This is the case where banks that face bad options take desperate bets, accepting unfavorable odds of making things worse in exchange for a small hope of avoiding a substantial loss. Our result suggests that this kind of behavior is inconsistent with the practice of big banks. Instead, the change from overweighting to underweighting of small probabilities helps explain the preference shift from risk aversion to risk seeking. In the crisis aftermath, banks perceived financial instability and bankruptcy threat to be over and reverted to underweighting the likelihood of tail losses as they did before the crisis.

Because banks in our sample underwent a recapitalization process as the government response to large losses that pushed banks near bankruptcy, the shift in risk attitudes touches on literature that investigates how prior losses affect risk preferences. This field of finance has produced contradictory empirical evidence. For example, following a loss, agents become either more risk-seeking (Andrade and Iyer (2009); Langer and Weber (2008)), or more risk-averse (Liu et al. (2010); Shiv et al. (2005)). The theoretical work on dynamic choice under uncertainty has reaffirmed the same discrepancy. For example, when risk attitudes are history-dependent in Barberis et al. (2001) and Dillenberger and Rozen (2015) realized losses discourage agents' risk-taking. The interpretation is that in the aftermath of a painful loss, investors are particularly sensitive to additional setbacks, which increases risk aversion. Conversely, in Shefrin and Statman (1985) losses lead to more risk taking. However, recent evidence suggests that investors may respond differently to paper or realized losses. Imas (2016) demonstrate that participants take on more risk after a *paper* loss (if the loss has not been realized) and less risk after a realized loss.[4] One explanation of why banks that suffered realized losses prior to government intervention, behave in a risk-seeking manner after the intervention is that recapitalization encourages banks to perceive realized losses as paper losses. In turn, paper loss leads to risk seeking. One implication of this result is that banks facing hypothetical losses cannot imagine how they would actually respond and underestimate the extent to which they would hope to avoid losses.

At first glance, the fourfold result raises doubts about the robustness of the inverted S-curve of prospect theory across different information environments. The convex weighting function before the crisis is nearly the mirror image of concave distortions during the recapitalization, as banks shift from optimism to pessimism. Similarly, the weighting function after the recapitalization is a mirror image of the one before and during the CPP. Our findings suggest that prospect theory, which postulates invariable probability weighting, cannot adequately represent risk attitudes of the largest banks. Instead, a more flexible probability weighting function might account for the fourfold pattern.

Exploring this line of plausible causes of the fourfold pattern, Fehr-Duda and Epper (2011) argue that inconsistent probability weighting function may indicate stake-dependence, delay-dependence, or shifting reference points. For instance, Fehr-Duda et al. (2010) finds that the probability weighting function is sensitive to rising stakes, but not utility function. When the size of lottery gains increases, participants became less optimistic and more responsive to probabilities as the elevation of the weighting function decreases while curvature increases. Similarly, Abdellaoui et al. (2011) demonstrate that probability weights for gains are sensitive to the resolution of uncertainty. Their experiment confirms inverse S-shape for non-delayed lotteries, lotteries that are resolved and paid out in the present versus in the future period. However, the introduction of time delay generates probabilistic optimism and makes lotteries more attractive, so participants felt more optimistic when regarding chance. The observed optimism is a consequence of the increased elevation and sensitivity when assuming Gonzalez and Wu (1999) parametric probability weighting function.[5]

Both theoretically and empirically, Epper and Fehr-Duda (2017) show that probability weighting coupled with the timing of the consequences and uncertainty resolution can explain the coexistence of over and underweighting of rare extreme events. In particular, risk tolerance varies greatly depending on the length of the delay and the perception of uncertainty resolution. When the passage of time is irrelevant, the probability weighting function results in an inverse S-shape. Unfavorable tail events are overweighted when perceived to materialize in the short-run but may end up being underweighted when expected to take place in the distant future. In contrast, sequential resolution of uncertainty counteracts this effect, in that rare events are overweighted when uncertainty is perceived to unfold gradually over time and underweighted in one shot at a specific time in the future. Therefore, the convex or concave

[4]In the empirical setting, Imas (2016) distinguish between a realized loss (e.g., selling a losing stock or cashing out after a loss) and one that is not realized – a paper loss (e.g., holding a losing stock or not cashing out after a loss).

[5]In their experiment, the utility of money does not react to the delayed resolution of uncertainty, so the impact of time delay is entirely absorbed by the probability weighting function.

weighting function we find may be a consequence of how large banks perceive tail losses to be absorbed by capital buffers over time. The fourfold pattern suggests that fine-tuning prospect theory to accommodate dynamic probability weighting is a potentially rich vein for future research.

Some recent studies provide a coherent picture of investors' risk preferences by assuming a context-dependent weighting function. In salience theory of Bordalo et al. (2013), when market gains are salient, meaning larger or less likely than losses, investors' attention is drawn to positive market outcomes causing them to underweight losses and overweight gains. Conversely, investors are prone to overweight losses in situations of abnormal negative return realizations. Related to the fourfold pattern, the concave weighting function may arise when market gains are salient, and banks perceive equity to be sufficient to absorb potential losses. Likewise, the convex weighting function may reflect banks' belief in the inadequacy of equity buffer to cover losses.

Perhaps at the fundamental level, banks are both cautious and hopeful about market losses, thereby continually scanning the market environment for potential threats and opportunities. Banks' behavior may have both internal and external causes, or what Lopes and Oden (1999) describes as a dispositional factor and a situational factor. The dispositional factor describes motivations that predispose individuals to be typically oriented to achieve security (risk-averse) or to exploit potential (risk-seeking). In contrast, the situational factor relates their responses to immediate present needs and opportunities. In the long-run, banks' risk attitudes can be described as cautious-hopeful, in that they pay attention to the best-case and the worst-case market outcomes. As Lopes and Oden (1999) suggests, these two factors are sometimes aligned and sometimes conflicting, producing behavioral patterns in which risk-averse and risk-seeking preference simultaneously exist in the same individual's behavior. Therefore, in the next section, we explore plausible economic factors that may contribute to or predict the probability weighting of large banks.

4 Economic drivers of Kahneman-Tversky probability distortions

A significant challenge that is inherent in the previous discussion is that we need a better understanding of why banks might underweight or overweight tail losses in their decisions. We start this section by presenting quantitative results on the magnitude of balance sheet losses perceived by larges banks. As the wedge between subjective and objective losses depends on probability weighting, we further investigate economic drivers of probability distortions.

By definition, spectral risk measures are the subjective expectation of market losses or expected prospect value. In this way, these risk measures reflect certainty equivalent (CE) or sure loss banks implied by banks' probability weighting function. For linear probability weighting function $W(p) = p$ or constant risk spectrum $w(p) = 1$, objective or undistorted losses are equal to $1 - e^{(\mu^q + \sigma\sigma^q)\tau}$.[6] Therefore, the difference between subjective and objective losses

[6]This is straightforward to show as $\int_0^1 1 \cdot (1 - e^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}})dp = 1 - 0 -$

equals

$$E_{KT}(Loss) - E(Loss) = \underbrace{\mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau}}_{\text{1-objective loss}} \left(1 - \underbrace{\frac{\delta\gamma(\Phi(\sigma+\sigma^q)(1-\Phi(\sigma+\sigma^q)))^{\gamma-1}}{(\delta\Phi(\sigma+\sigma^q)^{\gamma} + (1-\Phi(\sigma+\sigma^q))^{\gamma})^2}}_{\text{KT distortion}} \right). \tag{18}$$

In this way, observed risk-taking behavior can be summarized by *loss* risk premium defined as the difference between the expected prospect value (CE) and expected value. Positive premium indicate risk aversion (overweighting), negative risk-seeking (underweighting), and zero risk neutrality (no over- or underweighting). This premium fluctuates either because actual losses rise, or because banks distort probabilities more heavily. In other words, either probability weighting or objective market conditions play a role in driving this wedge.

Figure 5 plots the density function of Kahneman-Tversky distortions. The zero thresholds imply that subjective expectations of losses by large financial institutions coincide with objective losses, and risk premium is zero. Figure 5(b) illustrates that during the CPP, banks systematically overweighted losses, reaching a peak of 40%. This substantial overweighting is in stark contrast with approximately 12% underweighting after the CPP (Figure 5(b)). Most likely, banks perceived crisis period to be over. During peaceful times before the crisis, banks engage in both overweighting and underweighting of market losses. These three patterns are visible in Figure 4, where values above the dashed 45-degree line plot overweighted losses, and below the line underweighted losses.

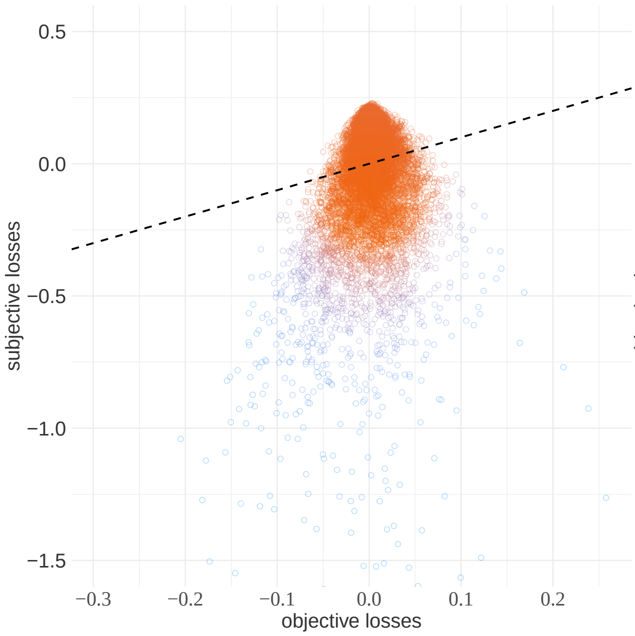
We continue our analysis of probability weighting by running fixed-effects regressions of Kahneman-Tversky probability distortions on combinations of the risk, liquidity, investor sentiment, and uncertainty variables. Except for the fourth group, these variables are predictors of excess stock return and equity premium in finance literature. Recall that in section 2.2, we have defined salience loss premium, $\xi q_t M_t$, as an extra compensation that banks demand above the equity risk premium to hold the risky security instead of a risk-free asset. Equivalently, equity premium or excess return can be decomposed to the sum of equity risk premium and salience loss premium. Therefore, our results have direct implications on the role of probability distortions in predicting excess return.

Risk variables are grouped into second, third, or fourth moments proxies. The second-moment variables are idiosyncratic risk (volatility), systematic risk (S&P volatility), and market beta. We estimate betas from rolling regressions of excess returns on market excess returns over 22 trading days.[7]. The same period applies when calculating third-moment proxies skewness of daily returns in the past 22 days and fourth moment proxy of historical Value at Risk at 15%. Conditional skewness is computed following Harvey and Siddique (2000) as the covariance between the excess return of asset j and squared excess return on the market .[8] For liquidity

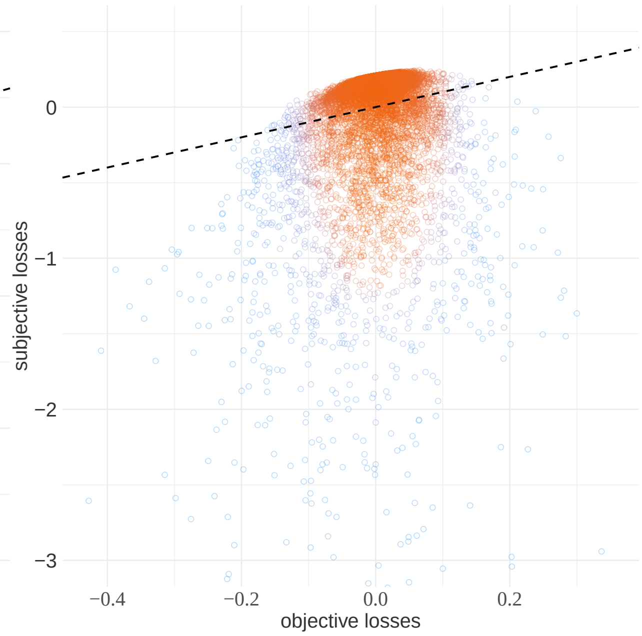
$\mathrm{e}^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau} \int_0^1 \mathrm{e}^{\Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}} dp = 1 - \mathrm{e}^{(\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma+\sigma_t^q)^2)\tau} \mathrm{e}^{\frac{1}{2}(\sigma+\sigma_t^q)^2\tau} = 1 - \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau}$.

[7]To reduce the impact of outliers, we follow Frazzini and Pedersen (2014) and shrink the time series beta estimates toward the cross-sectional mean of 1 using a scaling factor of 0.6, so $\hat{\beta} = 0.6\beta + 0.6 \cdot 1$.

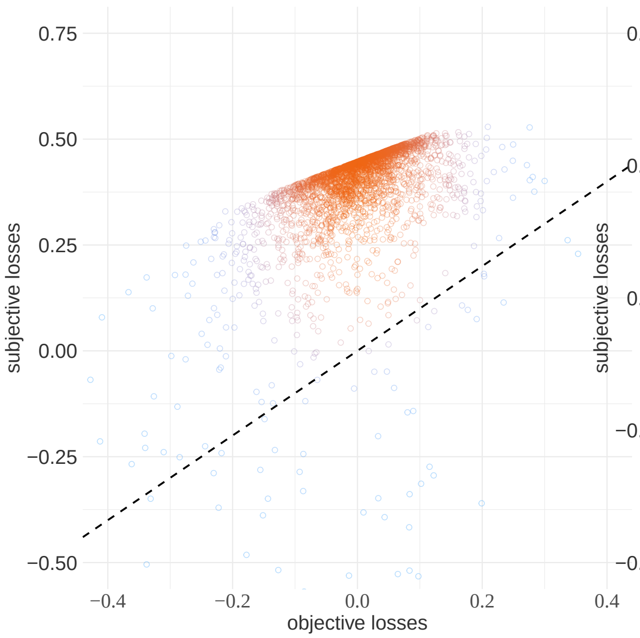
[8]In econometric terms, market beta $\beta_{j,t}$ and co-skewness $\delta_{j,t}$ are obtained from rolling window regressions



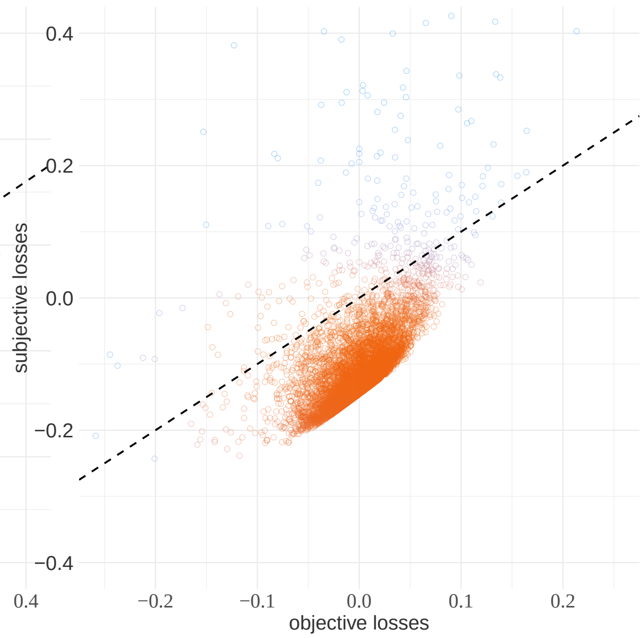
(a) Before the CPP



(b) Before-during the CPP



(c) During the CPP

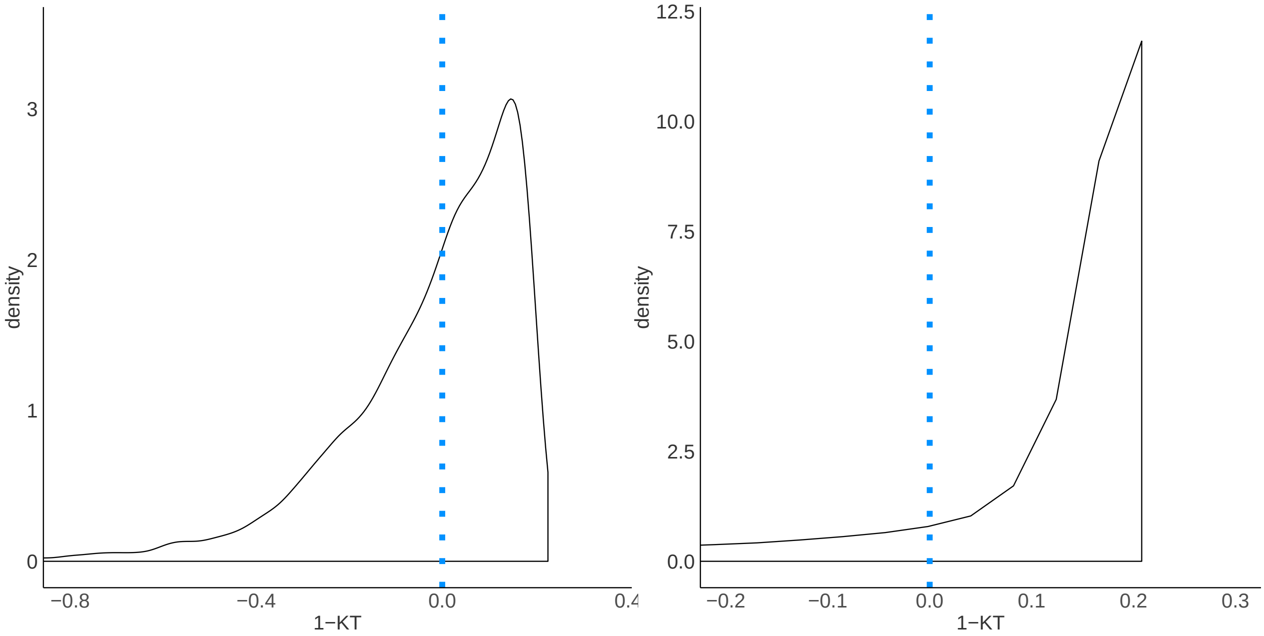


(d) After the CPP

Figure 4: Subjective versus objective losses

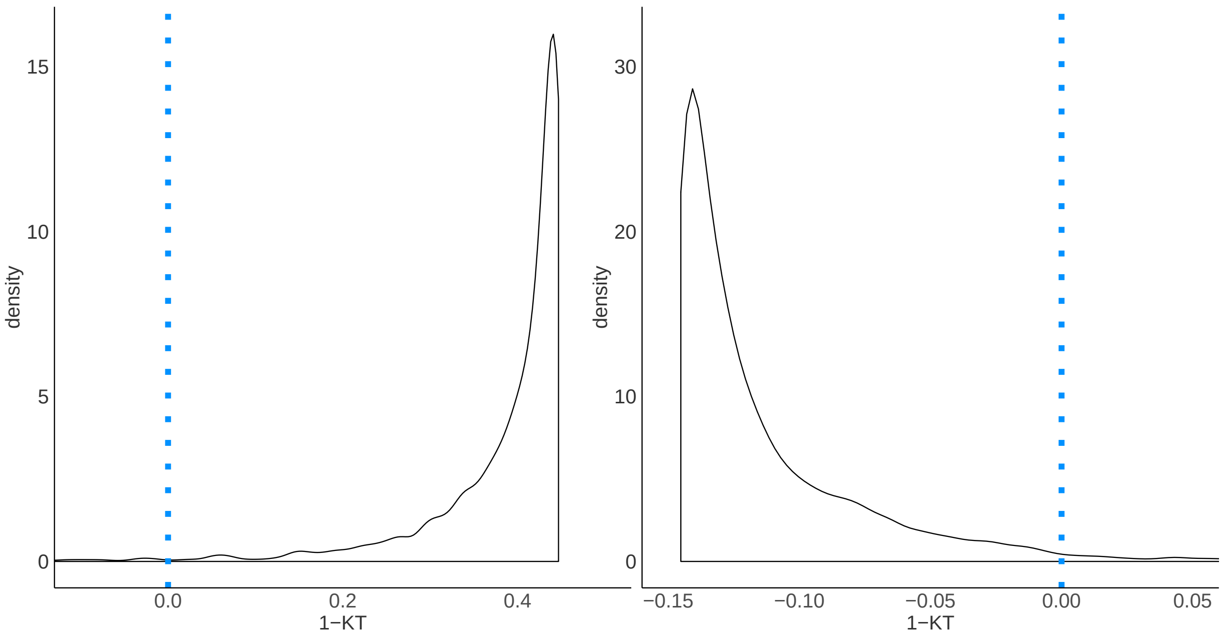
measures, funding conditions are represented by the TED spread and corporate bonds spread, and we choose Amihud (2002)'s measure of market liquidity. As such, market illiquidity of a security at time t is $ILLIQ = \frac{1}{22}\sum_{i=0}^{21} \frac{r_{t-i}}{VOLD_{t-i}}$, where r_t is the stock return and $VOLD_t$ is volume in 100 million dollars. In this interpretation, the stock is less liquid if a given trading volume generates a greater move in its price. We include the historical ILLIQ measure, which is to be

$R_{j,t+1} = \alpha_{j,t} + \beta_{j,t} R_{M,t+1} + \delta_{j,t} R^2_{M,t+1}$.



(a) Before the CPP

(b) Before-during the CPP



(c) During the CPP

(d) After the CPP

Figure 5: Risk attitudes and Kahneman-Tversky distortion

consistent with other measures the 22 trading days (i.e., one month) moving average of daily illiquidity.

We use four variables to investigate the relationship between investor sentiment and probability distortions. First, we employ mispricing factors of Stambaugh and Yuan (2017). The motivation is that expected returns and equity premium can be decomposed into systematic risks for which investors require remuneration, and mispricing components or anomalies such as market-wide investor sentiment. The first cluster, MGMT, represents components that a firm's management can affect somewhat directly and combines net stock issues, composite equity issues, net operating assets, asset growth, and investment to assets and accruals. The second cluster PERF is linked to the firm's performance and less directly controllable by management and includes distress, O-score, momentum, gross profitability, and return on assets. Another variable that captures the degree of market-wide mispricing is betting against beta (BAB) factor of Frazzini and Pedersen (2014). In their paper, high-beta stocks are overpriced because of excess demand from leverage constrained investors or lottery demanders that puts upward pressure on prices. The BAB strategy buys low-beta security and short sells high-beta stocks, consistent with exploiting the beta anomaly. Therefore, BAB proxies for the spread between underpriced and overpriced stocks. Our fourth variable in this cluster is MAX or 15 % tail return realizations over the past 22 days, which measures lottery demand.

To proxy for movements in policy-related economic uncertainty and the equity market, we follow Baker et al. (2016) who construct the Index of Equity Market Uncertainty (EMU) and index of policy-related Economic Uncertainty (EPU).[9] Baker et al. (2016) analyze newspaper coverage and articles containing terms related to uncertainty. In particular, the frequency of news articles containing the terms 'uncertainty' or 'uncertain ', 'economic' or 'economy' is registered in both indexes. Terms related to monetary, fiscal, and regulatory policy enter the EPU index, while stock market terms are included in the EMU index.

Table 10 reports results for the estimated effects of risk, liquidity, mispricing and lottery demand, and uncertainty factors on probability distortions. In all regressions add six Fama-French factors as additional controls, namely market (MktRF), size (SMB), value (HML), investment (CMA), profitability (RMW) and momentum (MoM).

First, we test predictions for the time series of risk measures. Before and during the CPP in column (1), the results suggest that large banks are sensitive to rare adverse events or market outcomes. If recent tail losses increase by 1 %, banks start overweighting potential losses by 0.06 % as estimates on the VaR coefficient suggest. As for other measures of risk, overweighting declines when return distribution becomes more skewed. As skewness is often associated with fear (for losses) or hope (for gains), banks become more hopeful about seizing high returns, which makes them less risk-averse towards losses. However, systematic skewness (coskewness) is positively correlated with overweighting. Therefore, variations in idiosyncratic or systematic skewness elicit opposite risk attitudes. A similar result holds for volatilities. The rise in bank-specific volatility by 1 % leads to compression of risk aversion by 1.45 %. As emphasized by Kumar (2009), investors perceive low-priced stocks with high idiosyncratic skewness and idiosyncratic volatility as gambles or lotteries. In contrast, when market volatility or beta increases by 1 %, overweighting rises by 0.25 %.

We can further see in column (2) of Table 10 that the level of the TED spread and corporate bond spread are negatively related to overweighting. An increase in 1 % in the interbank borrowing rate leads to an approximately 0.3 % percent decrease in observed risk aversion. Similarly, tight funding conditions in the corporate bonds market lead to a contraction in the

[9] Data series for both indexes can be accessed and downloaded at https://www.policyuncertainty.com/.

required risk premium by 0.11 %. Banks' response to heightening market illiquidity is only a 0.045 percent decline in overweighting. Since the TED spread measures the tightness of funding constraints or indicates that banks' funding constraints are worsening, negative correlation implies that the largest banks reduce overall overweighting because they are credit-constrained.

Turning to investors' sentiment, the question is, can mispricing and demand for lottery-type stocks explain probability distortions of the largest banks? Column (3) shows that the estimated coefficients for the BAB spread and mispricing factors related to banks' management MGMT are positive but statistically insignificant. However, performance positively affects overweighting. The estimated coefficient of 0.09 is most likely absorbing distress component of the PERF factor, suggesting that distressed banks and banks likely to go bankrupt soon (O-score variable) become more risk-averse. Profitability, momentum, and stock return components of the PERF factor are likely to have an opposite effect on banks' perceptions. Since we control for six Fama-French factors, including the profitability factor (RMW) and momentum factor (MoM), we find RMW and MoM estimate to be insignificant (p-value = 0.723 and p-value = 0.106 respectively). Moreover, sign on momentum estimate is negative,-0.058, so momentum might indicate that lottery demand reduces overweighting. Indeed, we find that idiosyncratic lottery demand is significantly contributing to a decrease in risk aversion. Roughly 0.1 % decline occurs when banks' extreme positive returns rise by 1 percent, as the MAX coefficient suggests.

In column (4), the results indicate the negative relationship between overweighting and current uncertainty and the positive effect of changes in uncertainty. An increase in 1 % of current policy or market uncertainty contributes to 0.19 % and 0.13 % decline in overweighting. In contrast, past policy uncertainty elicits the risk aversion to rise by 0.11 %. Conditions of high uncertainty stipulate banks to move in the direction of risk neutrality while worsening moves them away from neutrality. Overall, the role of news-based policy uncertainty in probability distortions seems to be more critical than uncertainty related to equity markets.

If the government is reluctant to bail out banks, the Fed is silent on lowering the interest rate or regulators indecisive about reducing capital requirements, this lack of transparency may push banks to respond with delay and employ a speculative strategy. The bank's initial reaction is to under-react but subsequently, overreact in response to news about an ambiguous policy stance. What such results imply is the substantial economic effects of monetary, fiscal, and regulatory policy uncertainty on how major financial institutions perceive and evaluate losses. If the government is firm in its decision and communicates it clearly, this may reassure banks about government backing in the long-run and mute overreaction. Government disclosure affects market risk perception; it is beneficial in the long-run, consistent with Moris and Shin (2002) claim of the social value of monetary authorities' transparency. As such, the EPU index is possibly a proxy for information asymmetry between banks and policymakers. When interpreting current period estimates, we caution that our results are silent on whether uncertainty is the cause or effect of risk perceptions of large banks. Mortgage-backed security losses of these financial institutions were central in the onset and resolution of the crisis by the government and have likely affected news coverage.

Finally, in the period after the government intervention, banks revert to underweighting, as suggested by Figure 5. A rise in the Ted spread, bank-specific volatility, and market volatility implies a decrease in underweighting. In contrast, the effect of other variables is substantially muted or insignificant compared to before-during the CPP period. Interestingly, now the coefficient on the BAB spread is significant and negative around -0.011. This finding suggests that underweighting of market losses by large banks might be due to constrained or lottery perusing behavior.

To summarize this section, our result suggests that in the period before and during the government recapitalization program, factors such as market volatility, beta, systematic skewness, and mispricing exacerbate overweighting of large banks. Interbank funding illiquidity, bank-specific volatility, and lottery demand have damping effects. Economic policy and market uncertainty initially lead to underweighting and subsequently overweighting of market losses.

Some of these factors have been associated with cross-sectional returns and equity premiums, while other factors have been recently applied in the literature that explores macro-financial linkage. For example, Stambaugh and Yuan (2017) demonstrate the ability of mispricing factors to explain expected returns in addition to systematic risks for which investors require compensation. Frazzini and Pedersen (2014) provide evidence that the overpricing of high-beta stocks is driven by funding liquidity. Harvey and Siddique (2000) show that stocks with high systematic skewness of returns have higher expected returns. A central tenet of higher-moments CAPM model is that stocks include rewards for accepting tail risk because investors put additional emphasis on the worst states of the market. Using firm-level data, Baker et al. (2016) find that policy uncertainty raises stock price volatility and infer that policy-related events have caused an increasingly large share of large stock movements. In our specification, an increase in bank-specific volatility may be a plausible channel through which policy uncertainty immediately affects probability distortions.

5 Conclusion

The empirical study of theories of decision under risk has been an active research field in experimental behavioral finance. The primary purpose of this paper is to devise a financial market approach to analyze prospect theory. For this reason, this study presents the estimation of prospect theory's subjective probability weighting functions and the degree of the financial constraint of large banks. Our contribution provides a novel perspective on the well-known psychology of tail events of prospect theory.

First, contrary to prospect theory, we do not find support for the consistency of the probability weighting function of large banks that were recapitalized by the government under the Capital Purchase Program. Instead, the fourfold pattern emerges: the weighting function during four periods is concave, convex, concave-convex, and convex-concave. Before the Great Recession, the largest banks tended to underweight the probability of tail losses, which generates the convex shape. During market turmoil and amid the CPP recapitalization, banks overweight the likelihood of the worst possible scenario. Merging the crisis and pre-crisis period generates an inverted S-curve of prospect theory, while the weighting function is S-shaped following the CPP. The second significant result is that banks are risk-averse in losses before and during government intervention, and risk-seeking afterward. Thirdly, we show that market volatility, skewness, lottery demand and mispricing, interbank funding liquidity, and economic policy are several underlying mechanisms for the overweighting and underweighting of tail events.

In conclusion, our results emphasize that probability weighting plays an essential role in explaining risk attitudes or large financial institutions. Moreover, we find that the evidence on the largest banks' behavior confirms the relevance of behavioral biases associated with tail events for asset pricing models. Generalizing the results beyond the scope of large and recapitalized banks is a valuable direction for future research.

References

Abdellaoui, M. (2000). Parameter-free elicitation of utility and probability weighting functions. *Management science*, 46(11):1497–1512.

Abdellaoui, M., Diecidue, E., and Öncüler, A. (2011). Risk preferences at different time periods: An experimental investigation. *Management Science*, 57(5):975–987.

Abdellaoui, M., Vossmann, F., and Weber, M. (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Management science*, 51(9):1384–1399.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1):31–56.

Andrade, E. B. and Iyer, G. (2009). Planned versus actual betting in sequential gambles. *Journal of Marketing Research*, 46(3):372–383.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Barberis, N. and Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5):2066–2100.

Barberis, N., Huang, M., and Santos, T. (2001). Prospect theory and asset prices. *The quarterly journal of economics*, 116(1):1–53.

Barberis, N., Jin, L. J., and Wang, B. (2019). Prospect theory and stock market anomalies. *Available at SSRN 3477463*.

Barberis, N., Mukherjee, A., and Wang, B. (2016). Prospect theory and stock returns: An empirical test. *The Review of Financial Studies*, 29(11):3068–3107.

Barseghyan, L., Molinari, F., O'Donoghue, T., and Teitelbaum, J. C. (2013). The nature of risk preferences: Evidence from insurance choices. *American Economic Review*, 103(6):2499–2529.

Booij, A. S., Van Praag, B. M., and Van De Kuilen, G. (2010). A parametric analysis of prospect theory's functionals for the general population. *Theory and Decision*, 68(1-2):115–148.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and asset prices. *American Economic Review*, 103(3):623–28.

Bruhin, A., Fehr-Duda, H., and Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, 78(4):1375–1412.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

De Giorgi, E. G. and Legg, S. (2012). Dynamic portfolio choice and asset pricing with narrow framing and probability weighting. *Journal of Economic Dynamics and Control*, 36(7):951–972.

Dillenberger, D. and Rozen, K. (2015). History-dependent risk attitude. *Journal of Economic Theory*, 157:445–477.

Epper, T. and Fehr-Duda, H. (2017). A tale of two tails: On the coexistence of overweighting and underweighting of rare extreme events.

Etchart-Vincent, N. (2004). Is probability weighting sensitive to the magnitude of consequences? an experimental investigation on losses. *Journal of Risk and Uncertainty*, 28(3):217–235.

Fehr-Duda, H., Bruhin, A., Epper, T., and Schubert, R. (2010). Rationality on the rise: Why relative risk aversion increases with stake size. *Journal of Risk and Uncertainty*, 40(2):147–180.

Fehr-Duda, H., De Gennaro, M., and Schubert, R. (2006). Gender, financial risk, and probability weights. *Theory and decision*, 60(2-3):283–313.

Fehr-Duda, H. and Epper, T. (2011). Probability and risk: Foundations and economic implications of probability-dependent risk preferences.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.

Gennaioli, N., Shleifer, A., and Vishny, R. (2012). Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics*, 104(3):452–468.

Goeree, J. K., Holt, C. A., and Palfrey, T. R. (2002). Quantal response equilibrium and overbidding in private-value auctions. *Journal of Economic Theory*, 104(1):247–272.

Gonzalez, R. and Wu, G. (1999). On the shape of the probability weighting function. *Cognitive psychology*, 38(1):129–166.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, 55(3):1263–1295.

Imas, A. (2016). The realization effect: Risk-taking after realized versus paper losses. *American Economic Review*, 106(8):2086–2109.

Kliger, D. and Levy, O. (2009). Theories of choice under risk: Insights from financial markets. *Journal of Economic Behavior & Organization*, 71(2):330–346.

Kőszegi, B. and Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, 64(4):1889–1933.

Langer, T. and Weber, M. (2008). Does commitment or feedback influence myopic loss aversion?: An experimental analysis. *Journal of Economic Behavior & Organization*, 67(3-4):810–819.

Liu, Y.-J., Tsai, C.-L., Wang, M.-C., and Zhu, N. (2010). Prior consequences and subsequent risk taking: New field evidence from the taiwan futures exchange. *Management Science*, 56(4):606–620.

Lopes, L. L. and Oden, G. C. (1999). The role of aspiration level in risky choice: A comparison of cumulative prospect theory and sp/a theory. *Journal of mathematical psychology*, 43(2):286–313.

O'Donoghue, T. and Somerville, J. (2018). Modeling risk aversion in economics. *Journal of Economic Perspectives*, 32(2):91–114.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, 40(3):777–790.

Shiv, B., Loewenstein, G., Bechara, A., Damasio, H., and Damasio, A. R. (2005). Investment behavior and the negative side of emotion. *Psychological science*, 16(6):435–439.

Stambaugh, R. F. and Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, 30(4):1270–1315.

Stott, H. P. (2006). Cumulative prospect theory's functional menagerie. *Journal of Risk and uncertainty*, 32(2):101–130.

Sydnor, J. (2010). (over) insuring modest risks. *American Economic Journal: Applied Economics*, 2(4):177–99.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Tversky, A., Slovic, P., and Kahneman, D. (1990). The causes of preference reversal. *The American Economic Review*, pages 204–217.

Van de Kuilen, G. and Wakker, P. P. (2011). The midweight method to measure attitudes toward risk and ambiguity. *Management Science*, 57(3):582–598.

Yaari, M. E. (1987). The dual theory of choice under risk. *Econometrica: Journal of the Econometric Society*, pages 95–115.

A Omitted Proofs

Proof of Proposition 1. Recall that we defined market losses as $X_t - X_{t+\tau}$ and $VaR_p^{t,t+\tau}$ is the quantile with confidence level $1-p$ of market losses. In other words, $VaR_p^{t,t+\tau}$ is defined as

$$VaR_p^{t,t+\tau} = \inf\{L \geq 0 : P(X_t - X_{t+\tau} \geq L | \mathcal{F}_t) \leq p\} = (Q_{t,t+\tau}^p)^-,$$

where

$$Q_{t,t+\tau}^p = \sup\{L \in \mathbb{R} : P(X_{t+\tau} - X_t \leq L | \mathcal{F}_t) \leq p\}$$

is the quantile of the projected market gains over the horizon of length τ and $x^- = \max\{0, -x\}$. Then we have

$$\begin{aligned}
&P(X_{t+\tau} - X_t \leq L | \mathcal{F}_t) \\
&= P\left(X_t \exp\left(\int_t^{t+\tau} (\mu_s^q + \sigma\sigma_s^q - \frac{1}{2}(\sigma + \sigma_s^q)^2) ds + \int_t^{t+\tau} (\sigma + \sigma_s^q) dW_s\right) - X_t \leq L \quad | \mathcal{F}_t\right) \\
&= P\left(\exp\left((\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau + (\sigma + \sigma_t^q)(W_{t+\tau} - W_t)\right) \leq 1 + \frac{L}{X_t} \quad | \mathcal{F}_t\right) \\
&= P\left((\sigma + \sigma_t^q)(W_{t+\tau} - W_t) \leq \log(1 + \frac{L}{X_t}) - (\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau \quad | \mathcal{F}_t\right) \\
&= \Phi\left(\frac{\log(1 + \frac{L}{X_t}) - (\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau}{(\sigma + \sigma_t^q)\sqrt{\tau}}\right)
\end{aligned}$$

where the last equality follows from the fact that the random variable $(\sigma + \sigma_t^q)(W_{t+\tau} - W_t)$ is conditionally normally distributed with zero mean and variance $(\sigma + \sigma_t^q)^2\tau$, and $\Phi(\cdot)$ is the cumulative distribution of the standard normal distribution. Therefore, we have

$$\begin{aligned}
&P(X_{t+\tau} - X_t \leq L | \mathcal{F}_t) \leq p \\
&\Phi\left(\frac{\log(1 + \frac{L}{X_t}) - (\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau}{(\sigma + \sigma_t^q)\sqrt{\tau}}\right) \leq p \\
&L \leq X_t \left(\exp\left((\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma_t^q)\sqrt{\tau}\right) - 1\right)
\end{aligned}$$

which implies

$$Q_{t,t+\tau}^p = X_t \left(\exp\left((\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma_t^q)\sqrt{\tau}\right) - 1\right)$$

Finally, we obtain the expression which is stated in the proposition

$$VaR_p^{t,t+\tau} = q_t k_t \left(1 - \exp((\mu_t^q + \sigma\sigma_t^q - \frac{1}{2}(\sigma + \sigma_t^q)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma_t^q)\sqrt{\tau})\right).$$

□

PROOF OF PROPOSITION 2. We need to evaluate the following integral

$$
\begin{aligned}
M_{CU} &= \int_0^1 (ap^2+bp^2+c)(1-\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau+\Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}})dp \\
&= \underbrace{\int_0^1 (ap^2+bp^2+c)dp}_{=1} - \int_0^1 (ap^2+bp^2+c)\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau+\Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}}dp \\
&= 1-(I+II+III)
\end{aligned}
$$

which can be separated into the sum of three integrals. Let us first introduce the change of variables $\Phi^{-1}(p)=x$, $p=\Phi(x)$, $dp=\phi(x)dx$ in order to solve these integrals. The third integral is equal to

$$
\begin{aligned}
III &= c\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau}\int_{-\infty}^{\infty}\mathrm{e}^{(\sigma+\sigma_t^q)\sqrt{\tau}x}\phi(x)dx \\
&= c\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2\tau+\frac{1}{2}(\sigma+\sigma_t^q)^2\tau}\Phi(x-(\sigma+\sigma^q)\sqrt{\tau})\Big|_{-\infty}^{+\infty} \\
&= c\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q)\tau}
\end{aligned}
$$

, where we have used $\int \mathrm{e}^{nx}\phi(x)dx = \mathrm{e}^{\frac{n^2}{2}}\Phi(x-n)$[10] . The second integral is equal to

$$
II = b\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau}\int_{-\infty}^{\infty}\mathrm{e}^{(\sigma+\sigma_t^q)\sqrt{\tau}}\phi(x)\Phi(x)dx.
$$

Introducing the integration by parts $u=\Phi(x)$ $du=\phi(x)dx$, and $dv=\mathrm{e}^{(\sigma+\sigma_t^q)\sqrt{\tau}x}\phi(x)dx$, $v=\mathrm{e}^{(\sigma+\sigma_t^q)^2\tau/2}\Phi(x-(\sigma+\sigma^q)\sqrt{\tau})$, we have

$$
\begin{aligned}
II &= b\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau+\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau}\left(\Phi(x)\Phi(x-(\sigma+\sigma^q)\tau)\Big|_{-\infty}^{+\infty}-\int_{-\infty}^{\infty}\phi(x)\Phi(x-(\sigma+\sigma^q)\sqrt{\tau})dx\right) \\
&= b\mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q)\tau}(1-1+\Phi(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}})) = \mathrm{e}^{(\mu_t^q+\sigma\sigma_t^q)\tau}\Phi(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}})
\end{aligned}
,
$$

where we have used

$$
\begin{aligned}
&\int_{-\infty}^{+\infty}\Phi(x)\cdot\phi(m+sx)dx = \int_{-\infty}^{+\infty}\Phi(\frac{x-m}{s})\cdot\phi(x)\frac{dx}{s} \\
&= \frac{1}{s}\left(1-\Phi(\frac{m}{\sqrt{1+s^2}})\right).
\end{aligned}
$$

Analogously, using the integration by parts $u=\Phi^2(x)$ $du=2\phi(x)\Phi(x)dx$, and $dv=\mathrm{e}^{(\sigma+\sigma_t^p)\sqrt{\tau}x}\phi(x)dx$,

[10] See wikipedia: List of integrals of Gaussian functions.

$v = e^{(\sigma+\sigma_t^q)^2\tau/2}\Phi(x-(\sigma+\sigma^q)\sqrt{\tau})$ and using

$$\int_{-\infty}^{+\infty}\Phi(x)^2\cdot\phi(m+sx)dx = \int_{-\infty}^{+\infty}\Phi^2(\frac{x-m}{s})\cdot\phi(x)\frac{dx}{s}$$
$$= \frac{1}{s}\left(1-\Phi(\frac{m}{\sqrt{1+s^2}})\right) - \frac{2}{s}T\left(\frac{m}{\sqrt{1+s^2}},\frac{s}{\sqrt{2+s^2}}\right),$$

we find the third integral to be equal to

$$III = ae^{(\mu_t^q+\sigma\sigma_t^q)\tau}\left(\Phi(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}}) - T(\frac{(\sigma+\sigma^q)\sqrt{\tau}}{\sqrt{2}},\frac{1}{\sqrt{3}})\right),$$

which concludes the proof for M_{CU}.

We use Laplace's method to prove the expression for M_{KT}. In general case, Laplace method determines the leading-order behavior of the integral

$$I(\lambda) = \int_a^b f(x)e^{-\lambda g(x)}dx. \tag{19}$$

We assume that integral converges for λ sufficiently large, that f and g are smooth enough near to be replaced by local Taylor approximations of appropriate degree. Laplace's method postulates if g assumes a strict minimum over $[a,b]$ at an interior critical point c, then integral can be approximated by

$$I(\lambda) \approx e^{-\lambda g(c)}f(c)\sqrt{\frac{2\pi}{\lambda g''(c)}} \tag{20}$$

First let us introduce the change of variables $\Phi^{-1}(p) = x$. Therefore, $p = \Phi(x)$ and $dp = \phi(x)dx$, where $\phi(\cdot)$ is the pdf of the standard normal distribution.

$$\int_0^1 \frac{\delta\gamma(p(1-p))^{\gamma-1}}{(\delta p^\gamma+(1-p)^\gamma)^2}e^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau+\Phi^{-1}(p)(\sigma+\sigma_t^q)\sqrt{\tau}}dp$$
$$= e^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau}\int_{-\infty}^{\infty}\frac{\delta\gamma(\Phi(x)(1-\Phi(x)))^{\gamma-1}}{(\delta\Phi(x)^\gamma+(1-\Phi(x))^\gamma)^2}e^{(\sigma+\sigma_t^q)\sqrt{\tau}x}\frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}dx$$
$$= e^{(\mu_t^q+\sigma\sigma_t^q-\frac{1}{2}(\sigma+\sigma_t^q)^2+\frac{1}{2}(\sigma+\sigma_t^q)^2)\tau}\int_{-\infty}^{\infty}\frac{\delta\gamma(\Phi(x)(1-\Phi(x)))^{\gamma-1}}{(\delta\Phi(x)^\gamma+(1-\Phi(x))^\gamma)^2}e^{(\sigma+\sigma_t^q)\sqrt{\tau}x}\frac{1}{\sqrt{2\pi}}e^{-\frac{(x-(\sigma+\sigma_t^q)\sqrt{\tau})^2}{2}}dx$$

In our case, $\lambda = -1$, $f(x) = \frac{\delta\gamma(\Phi(x)(1-\Phi(x)))^{\gamma-1}}{(\delta\Phi(x)^\gamma+(1-\Phi(x))^\gamma)^2}$, $g(x) = e^{\frac{(x-(\sigma+\sigma_t^q)\sqrt{\tau})^2}{2}}$. Therefore, $g'(x) = (x-(\sigma+\sigma_t^q)\sqrt{\tau})e^{\frac{(x-(\sigma+\sigma_t^q)\sqrt{\tau})^2}{2}} = 0$ implies $c = (\sigma+\sigma_t^q)\sqrt{\tau}$. $g''(x) = ((x-(\sigma+\sigma_t^q)\sqrt{\tau})^2+1)e^{\frac{(x-(\sigma+\sigma_t^q)\sqrt{\tau})^2}{2}}$, so $g''(c) = 1$. Substituting these expressions in Laplace's approximation, we obtain expression for M_{KT}. □

PROOF OF PROPOSITION 3. First, let us now solve for banks' maximization problem. Banks'

Hamilton-Jakobi-Bellman equation is

$$\rho V(n_t) = \max_{c_t,k_t} \quad \log c_t + V'(n_t)[Ak_t + r_t n_t + q_t k_t(\mu_t^q + \sigma\sigma_t^q - r_t) - c_t] + \frac{1}{2}V''(n)(\sigma + \sigma_t^q)^2 q_t^2 k_t^2 + \xi\left[n_t - q_t k_t M\right]. \tag{21}$$

The optimal policies for consumption and capital demand are computed from two optimality conditions and the Lagrange multiplier ξ on the expected loss constraint.

$$\frac{1}{c_t} = V'(n_t) \tag{22}$$

$$\frac{A}{q_t} + \mu_t^q + \sigma\sigma_t^q = r_t + \frac{-V''(n_t)(\sigma + \sigma_t^q)^2 q_t k_t + \xi q_t M}{V'(n_t)} \tag{23}$$

$$\xi(n_t - q_t k_t M) = 0. \tag{24}$$

In order to obtain asset pricing equation (23) we need to solve for banks' optimal consumption from Euler equation by using the method of matching drifts. Let $\lambda = V'(n)$ represent banks' stochastic discount factor and let it follow Brownian motion

$$d\lambda = \mu^\lambda \lambda dt + \sigma^\lambda \lambda dW_t$$

By Ito's lemma using $\lambda = V'(n)$ we have

$$\mu^\lambda \lambda = V''(n)[Ak + r_t n + qk(\mu^q + \sigma\sigma^q - r_t) - c] + \frac{1}{2}V'''(n)(\sigma + \sigma^q)^2 p^2 k^2$$

$$\sigma^\lambda \lambda = V''(n)(\sigma + \sigma^q)qk$$

The envelope condition of banks is

$$\begin{aligned}
\rho V'(n) &= \left(\log c - V'(n)c\right)' + \left(V'(n)\left[A\frac{n}{qM} + r_t n + \frac{n}{M}(\mu^q + \sigma\sigma^q - r_t)\right]\right)' \\
&\quad + \frac{1}{2}\left[V''(n)(\sigma + \sigma^q)^2 \frac{n^2}{M^2}\right]' + \xi'(n)\left[n - qkM\right] + \xi(n)\left[n - qMk(n)\right]' \\
&= \left(\frac{1}{c}c'(n) - V'(n)c(n) - V''(n)c\right) + V''(n)\left[A\frac{n}{qM} + r_t n + \frac{n}{M}(\mu^q + \sigma\sigma^q - r_t)\right] \\
&\quad + V'(n)\left[r_t + \frac{1}{M}(A + \mu^q + \sigma\sigma^q - r_t)\right] + V''(n)\left[(\sigma + \sigma^q)^2 \frac{n}{M^2}\right] \\
&\quad + \frac{1}{2}\left[V'''(n)(\sigma + \sigma^q)^2 \frac{n^2}{M^2}\right]
\end{aligned}$$

The equality follows from the fact that the constraint is binding and when substituting for $k = \dfrac{n}{qM}$. Using the first order condition for consumption and expression for drift and volatility of the stochastic discount function we get the rewritten envelope condition

$$\rho - \frac{1}{M}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) - r_t = \mu^\lambda + (\sigma + \sigma^q)\frac{\sigma^\lambda}{M}.$$

Therefore, the stochastic discount factor of intermediaries evolves as

$$\frac{d\lambda}{\lambda} = \left(\rho - r_t - \frac{1}{M}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) - (\sigma + \sigma^q)\frac{\sigma^\lambda}{M}\right) dt + \sigma^\lambda dW_t$$

giving us the expression for the drift of the SDF

$$\mu^\lambda = \rho - r_t - \frac{1}{M}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) - (\sigma + \sigma^q)\frac{\sigma^\lambda}{M}. \tag{25}$$

We can also rewrite the first order condition for capital presented in the main text, that is the bank's asset pricing equation

$$\lambda\left(A + q(\mu^q + \sigma\sigma^q - r_t)\right) + (\sigma + \sigma^q)\sigma^\lambda \lambda q - \xi q M = 0. \tag{26}$$

Then we get that banks' stochastic discount factor which differs from households' exactly in the third term

$$\mu^\lambda = \rho - r_t - \frac{\xi}{\lambda}.$$

The first order condition with respect to consumption is $c = \frac{1}{\lambda}$. Using Ito's lemma we obtain the expressions for consumption growth and volatility

$$\mu^c = -\mu^\lambda + (\sigma^\lambda)^2, \quad \sigma^c = -\sigma^\lambda. \tag{27}$$

We also know by Ito's lemma $c(n)$

$$\mu^c c = c'(n)[Ak + r_t n + qk(\mu^q + \sigma\sigma^q - r_t) - c] + \frac{1}{2}c''(n)(\sigma + \sigma^q)^2 p^2 k^2, \tag{28}$$

$$\sigma^c c = c'(n)(\sigma + \sigma^q)qk = c'(n)(\sigma + \sigma^q)\frac{n}{M}. \tag{29}$$

Now we match consumption drifts using (28),(29),(27),(26), and (25) we get

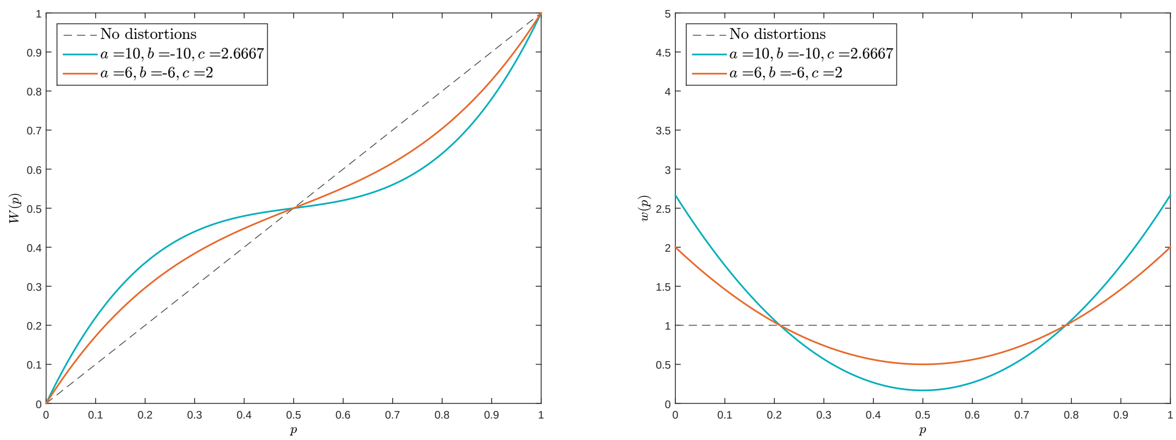
$$r_t - \rho + \frac{1}{M}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) + \frac{(\sigma + \sigma^q)}{M}\left(-\frac{c'(n)(\sigma + \sigma^q)\frac{n}{M}}{c(n)}\right) + \left(-\frac{c'(n)(\sigma + \sigma^q)\frac{n}{M}}{c(n)}\right)^2$$
$$= \frac{c'(n)[\frac{n}{M}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) + r_t n - c(n)] + \frac{1}{2}c''(n)(\sigma + \sigma^q)^2\frac{n^2}{M^2}}{c(n)}.$$

Guessing a linear consumption rule we get $c(n) = An + F$ and substituting it in matching drifts we get $c(n) = \rho n$. Using Euler equation (22), we have $V'(n) = \frac{1}{\rho n}$, and $V''(n) = -\frac{1}{\rho n^2}$. Finally, plugging back expressions for $V'(n), V''(n)$ into asset pricing equation (23), we obtain the asset pricing equation from the main text, which concludes the proof. □

B Robustness check for probability weighting function

Figure 6(a) and (b) illustrate the cubic probability weighting function and quadratic risk spectrum for different values of a, b, and c. The dashed 45-degree line corresponds to the linear probability weighting of the expected utility theory. Similar to prospect theory, the cubic weighting function can capture an inverse S-shape. As in section 3.3, we now estimate coefficients a and b, of the cubic probability weighting function and Lagrange multiplier ξ from the asset pricing equation (15) and expression for risk measure M_{CU} (17) by the general method of moments.

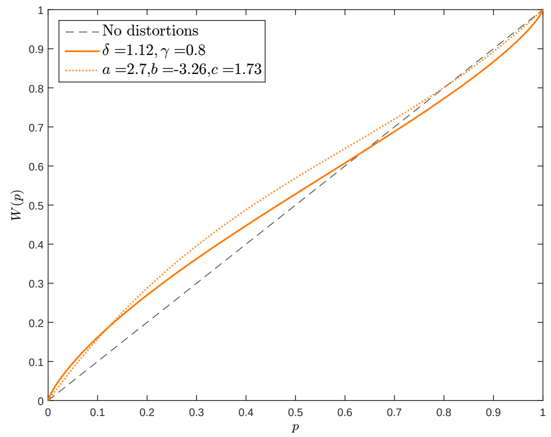
Table 11 presents the results of GMM estimation for various combinations of Fama-French factors as instruments. As before, notation Y indicates if the instrument is used in estimation. Figure 6(a) and (b) depict probability weighting functions estimated with five Fama-French factors as instruments (MktRF, SMB, HML, RMW, and CMA) before and during CPP, and after CPP. As a reference, we plot estimated Kahneman-Tversky probability weighting functions during the same periods from section 3.4. Before and during the CPP, the estimated coefficients a and b have values ranging from 2.27 to 2.7 and from -3.31 to -3.25, respectively. After the recapitalization, a is negative and takes values between -3.03 and -2.78, while b is positive and ranges from 2.58 to 2.96. In all estimations, ξ is positive or negative, but insignificant. Compared to the weighting functions from section 3.4, the cubic function is slightly more elevated before and during the CPP, indicating a higher degree of overweighting. After the CPP, two weighting functions are almost indistinguishable in the region of small probabilities between 0 and 0.4.



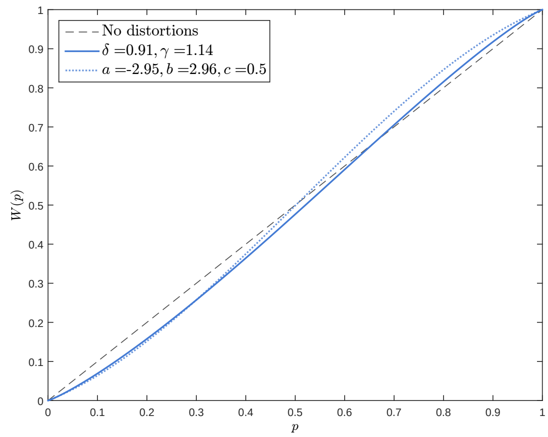
(a) Cubic probability weighting function

(b) Quadratic risk spectrum

Figure 6: Polynomial distortions. *Notes*: The left panel plots the cubic probability weighting function, $W(p) = \frac{a}{3}p^3 + \frac{b}{2}p^2 + cp$ for various parameter values of a, b and c. The right panel plots the associated quadratic risk spectrum $w(p) = W'(p)$.



(a) Before and during the CPP



(b) After the CPP

Figure 7: Estimated cubic probability weighting function. *Notes*: The dotted orange line in left panel plots the cubic probability weighting function $W(p) = \frac{a}{3}p^3 + \frac{b}{2}p^2 + cp$ for estimated parameter values of a, b and c before and during the Capital Purchase Program (January 2nd, 2007 - December 26th, 2008). The solid orange line in left panel plots the probability weighting function of Gonzalez and Wu (1999), $W(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$, for estimated parameter values of δ and γ in the same period. The doted and solid blue lines in right panel plot two probability weighting functions for estimated parameter values after the Capital Purchase Program (January 2nd, 2010 - December 31st, 2010).

Table 10: Economic drivers of Kahneman-Tversky distortion

This table presents the results from fixed-effects time-series regressions. The left-hand side variable is the Kahneman-Tversky probability distortion. Computed explanatory variables include idiosyncratic skewness, market beta, prior gains (MAX), and losses (VaR) in the top 15th percentile. ILLIQ is market illiquidity is computed as in Amihud (2002). To construct conditional skewness, we follow Harvey and Siddique (2000). MGMT and PERF are mispricing factors of Stambaugh and Yuan (2017), BAB is the betting against beta factor of Frazzini and Pedersen (2014), and EPU and EMV are news-based Economic Policy Uncertainty Index and Economic Market Uncertainty Index of Baker et al. (2016). All regressions include time fixed effects and six Fama-French factors as controls, namely MktRF, SMB, HML, RMW, CMA, and MoM. Standard errors robust to heteroskedasticity and autocorrelation are reported in parentheses. The sample periods are before-during the CPP (January 2nd, 2007, through December 26th, 2008) and after the CPP (January 2nd, 2010, through December 31st, 2010).

	$1-KT$							
	before and during the CPP				after the CPP			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
volatility	-1.457^{***}				0.215^{***}			
	(0.151)				(0.002)			
volatility SP500	0.259^{*}				0.076^{***}			
	(0.146)				(0.008)			
skewness	-0.020^{**}				0.0001			
	(0.010)				(0.0003)			
co-skewness	0.073^{***}				-0.001^{**}			
	(0.022)				(0.0004)			
beta	0.253^{***}				-0.004^{***}			
	(0.039)				(0.001)			
VaR	0.061^{***}				0.001			
	(0.012)				(0.0003)			
TED spread		-0.302^{***}				0.143^{***}		
		(0.042)				(0.017)		
AAA-Treasury		-0.118^{***}				-0.016^{***}		
		(0.037)				(0.005)		
ILLIQ		-0.045^{***}				-0.005^{***}		
		(0.007)				(0.001)		
MAX			-0.109^{***}				0.018^{***}	
			(0.010)				(0.002)	
BAB			0.033				-0.011^{**}	
			(0.044)				(0.005)	
MGMT			0.051				0.010	
			(0.041)				(0.008)	
PERF			0.097^{***}				-0.010^{**}	
			(0.033)				(0.005)	
log(EMU)				-0.134^{***}				0.006^{**}
				(0.019)				(0.003)
Δlog(EMU)				0.053^{***}				-0.006^{**}
				(0.014)				(0.002)
log(EPU)				-0.192^{***}				-0.010^{**}
				(0.025)				(0.005)
Δlog(EPU)				0.116^{***}				0.005
				(0.025)				(0.005)

Table 11: GMM estimation of cubic probability weighting function

This table reports the results of restricted GMM estimation of coefficients a and b of cubic probability weighting function and the Lagrange multiplier ξ the from the bank's asset pricing equation. The instruments considered are the seven Fama-French factors : size (SMB), value (HML),profitability (RMW), investment (CMA), momentum (MoM) and two book-to-market factors, Lo30 and Med40. Notation Y indicates if an instrument is used in estimation. Robust standard errors are reported in parentheses. The sample periods are before-during the CPP (January 2nd, 2007, through December 26th, 2008) and after the CPP (January 2nd, 2010, through December 31st, 2010).

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
a	2.704***	2.704***	2.278***	$-$2.949***	$-$2.787***	$-$3.038***
	(0.003)	(0.003)	(0.008)	(0.002)	(0.015)	(0.004)
b	$-$3.256***	$-$3.256***	$-$3.310***	2.961***	2.582***	2.587***
	(0.003)	(0.003)	(0.009)	(0.002)	(0.016)	(0.004)
ξ	0.085	0.093	0.484	0.198	$-$0.200	$-$0.450
	(0.217)	(0.197)	(0.441)	(7.572)	(35.896)	(3.047)
MktRF	Y			Y		
SMB	Y	Y	Y	Y	Y	Y
HML	Y	Y	Y	Y	Y	Y
RMW	Y	Y	Y	Y	Y	Y
CMA	Y	Y	Y	Y	Y	Y
MoM			Y			Y
Lo30		Y				
Med40					Y	
J-test p-value	0.99	0.99	0.95	0.99	0.94	0.99
Observations	16,670	16,670	16,670	9,249	9,249	9,249

Note: *p$<$0.1; **p$<$0.05; ***p$<$0.01