Probability Overweighting or Underweighting? Evidence From Systemically Important Banks

Branka Matyska*
De Nederlandsche Bank

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Abstract

This paper empirically tests theories of the psychology of tail events, in particular prospect theory. We develop a model where banks use subjective expectations and probability weighting to measure market risk on their balance sheet. Then, we estimate the probability weighting function derived from the asset pricing equation of the largest banks that were recapitalized under the Capital Purchase Program. Our findings reveal that banks demonstrate the coexistence of over- and underweighting of tail losses. Specifically, banks tend to overweight small probability losses during the financial distress and underweight the same when not exposed to insolvency risk. Before and during recapitalization, banks overweight low probability losses and underweight high probability losses, consistent with an inverse S-shaped probability weighting function of prospect theory. However, after the recapitalization, banks revert to underweighting tail events. This behavioral bias appears to be associated with funding liquidity, prior gains and losses, market risk, investor sentiment, default probabilities, and policy uncertainty.

*Dutch Central Bank, Research Department, Westeinde 1, Amsterdam; b.matyska@dnb.nl.

1 Introduction

Asset pricing models rely on a crucial assumption regarding how investors perceive and evaluate risks. Expected utility theory, a pillar of rational decision-making in uncertain environments, assumes that investors assess risks by linearly weighting probabilities. However, research in behavioral economics, notably Tversky and Kahneman (1992)'s prospect theory, has revealed that investors' behavior substantially deviates from the assumptions of expected utility. According to prospect theory, decision-makers use subjective probabilities instead of objective probabilities to guide their decisions - they overweight small probability events and underweight high probability outcomes. As a result of probability weighting, decision-makers may exhibit risk aversion in some situations and have risk-seeking preferences in other circumstances.[1] This raises an important question: are probability distortions stable over time, and what factors contribute to such behavioral bias?

This paper tests prospect theory predictions in the asset pricing model of liquidity-constrained banks. The first question is, do large banks overweight or underweight tail losses? Second, which factors are associated with underweighting or overweighting? To address the first question, we estimate the probability weighting function across periods preceding, during, and following government intervention. This allows us to focus on both constraint-binding and non-binding phases. Notably, during the 2008 financial crisis, the Troubled Asset Relief Program (TARP) was implemented to stabilize the US financial system. A critical component of TARP was the Capital Purchase Program (CPP), which aimed to alleviate liquidity constraints by injecting capital into financially distressed institutions. To address the second question, we investigate five groups of potential factors that may contribute to probability distortions: market risk, default probabilities, funding liquidity, investor sentiment, and policy uncertainty.

The first part of the paper integrates probability weighting into the conventional consumption-based asset pricing model. Banks derive utility from consumption while facing capital requirement constraint to hold enough capital to cover expected losses. Our model specification is further motivated by probability distortions in Yaari (1987) and Tversky and Kahneman (1992). Similar to prospect theory, banks mentally distinguish between gains and losses associated with investing in risky assets. Subsequently, they evaluate this assessment – the distribution of gains and losses – to compute subjective expected losses. Within our framework, banks distort probabilities in line with prospect theory when computing expected losses. In the second part of the paper, we estimate parameters of the probability weighting function using the asset pricing equation and generalized method of moments.

This paper contributes to the existing literature on estimating the probability weighting function of prospect theory. While prior studies predominantly rely on experimental settings, they consistently find robust evidence supporting an inverse S-shaped probability weighting, particularly in financial contexts (Abdellaoui (2000); Abdellaoui et al. (2005); Booij et al. (2010); Etchart-Vincent (2004); Fehr-Duda et al. (2006); Gonzalez and Wu (1999); Stott (2006); Tver-

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

sky and Kahneman (1992)). Among seminal contributions, Gonzalez and Wu (1999) observe a tendency among participants to overweight small probabilities and underweight large probabilities in lottery scenarios. Bruhin et al. (2010) reveal significant heterogeneity in risk-taking behavior, with only approximately 20% of participants adhering to expected utility maximization while the majority exhibiting nonlinear probability distortions. The potential significance of probability weighting extends beyond laboratory settings. In financial market environment, Kliger and Levy (2009) reveal probability weighting patterns in call option data that align with prospect theory. Sydnor (2010) analyzes household choices regarding deductible levels for property insurance policies and finds substantial evidence of probability distortions, particularly in the overweighting of low likelihood events of having to file a claim. Barseghyan et al. (2013) also emphasize the role of overweighting small probabilities in explaining risk aversion in deductible home insurance choices. In contrast to existing research, this paper focuses on the evaluation of tail events by large and systematically important financial institutions.

This paper also relates to the literature that applies probability weighting of prospect theory to asset pricing. Barberis et al. (2001) explores the implications of prospect theory for stock market anomalies, providing early evidence that prospect theory's probability weighting can explain various market phenomena. Building on this foundation, subsequent research by Barberis and Huang (2008) extends the analysis to incorporate the effects of prospect theory on investor behavior and market outcomes. De Giorgi and Legg (2012) further investigates the role of probability weighting in dynamic asset pricing models, shedding light on market non-participation puzzle and the equity premium puzzle. Baele et al. (2019) examines the implications of prospect theory for option pricing, revealing how probability weighting generate puzzlingly low returns on both out-of-the-money put and out-of-the-money call options. Recently, Barberis et al. (2019) synthesizes prospect theory's ability to explain a wide range of stock market anomalies, with factors like volatility, skewness, and past gains or losses affecting risk assessment and equity premiums. We expand on their analysis by adding liquidity, sentiment, policy uncertainty, and default probabilities. We focus particularly on recapitalized banks, where financial distress is a significant concern. Our rationale for including additional factors stems from the observation that distressed banks and market participants are more likely to consider government intervention policies and bank illiquidity when assessing tail risk. By exploring these factors, we aim to provide a more comprehensive understanding of how probability distortions and equity premiums are influenced in the context of recapitalized banks.

In summary, our findings reveal a nuanced interplay between overweighting and underweighting of tail events of systemic banks. Rather than observing stable weighting function, we find a dynamic pattern characterized by concave, convex, concave-convex (inverse S-shaped), and convex-concave (S-shaped) weighting functions across distinct periods. Prior to the 2008 financial crisis, major banks tended to underweight the likelihood of tail and highly probable losses, resulting in a convex weighting function. During times of financial distress and amidst the Capital Purchase Program recapitalization, banks exhibited a propensity to overweight small and high probability losses. Combining the pre-crisis and crisis period yields a standard inverted S-shaped weighting function of prospect theory, implying overweighting of small and underweighting of high probabilities. After the recapitalization, we observe S-shaped, indicating that banks underweight small probability losses and overweight highly probable losses. These findings contribute to the existing evidence on dynamic and context-dependent probability weighting. In salience theory of Bordalo et al. (2013), investors overweight losses when abnormal negative return realizations are salient. In contrast, when gains are salient, investors' attention is drawn to positive market outcomes causing them to underweight losses and overweight gains. Additionally, our findings align with Epper and Fehr-Duda (2017), which suggest that probability weighting varies in response to the timing of consequences and uncertainty resolution. According to their model, decision-makers' willingness to take risks depends on how long they must wait and how certain they are about the outcome. When time is irrelevant, decision-makers tend to overestimate the probability of negative rare events happening soon, but underestimate the probability of those events happening in the distant future. However, if the outcome is uncertain and will take time to unfold, they overestimate the chances of negative rare events happening. On the other hand, if they know when the outcome will be revealed, they tend to underestimate the chances of negative events. This might has implications for systemic banks, as they need to consider whether and when tail losses and government capital injections will materialize.

Furthermore, our findings indicate that the bank capital requirement constraint is binding during government recapitalization but becomes relaxed afterward. This result holds only after including Fama-French book-to-market factors. We jointly determine the probability weighting function and the Lagrange multiplier associated with the capital requirement constraint in our model. In the pre-crisis period, the Lagrange multiplier is insignificant, implying unconstrained systemic banks. However, during recapitalization, it becomes positive and significant, suggesting that banks were undercapitalized. Post-intervention, the Lagrange multiplier is significant and negative, implying the relaxation of the constraint. This relaxation of the constraint after recapitalization is associated with risk-seeking behavior over small probability losses. That said, our results shed light on the impact of prior losses on risk preferences among banks that underwent recapitalization following significant losses that brought them near bankruptcy. Prior literature suggests that agents tend to become either more risk-seeking (Andrade and Iyer (2009); Langer and Weber (2008)) or more risk-averse after a loss (Liu et al. (2010); Shiv et al. (2005)). However, recent research indicates that investors may respond differently to realized losses compared to paper losses. For instance, Imas (2016) show that participants tend to take more risk after a paper loss (if the loss has not been realized), while they take less risk after a realized loss. We propose that recapitalization encourages banks to view realized losses as paper losses, which may lead to risk-seeking preferences.

Lastly, we find that several factors amplify overweighting before and during government recapitalization programs, including prior losses, market volatility, beta, systematic skewness, and market-wide investor sentiment. Conversely, interbank funding illiquidity and prior gains can mitigate overweighting before recapitalization and amplify underweighting after recapitalization.[2] Interestingly, policy uncertainty and default probabilities can reduce the overweighting of tail market losses before a crisis but have little effect on subsequent underweighting after recapitalization. Based on these results, understanding risk attitudes during peaceful times versus distress periods may have implications for macroprudential regulation. To calibrate capital requirements and act as an early warning indicator of crises, regulators may estimate the probability weighting function in the tranquil period, particularly for systemically important institutions. This function can indicate excessive risk appetite or tail loss neglect in financial markets and give policymakers room to anticipate downturns and prepare responses when banks are not distressed. By estimating the probability weighting function when banks have ample liquidity or when there is a liquidity shortage, regulators can calibrate capital buffers to respond to 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 weighting function of the largest banks. Section 4 investigates economic drivers of probability distortions. Section 5 concludes.

2 Model

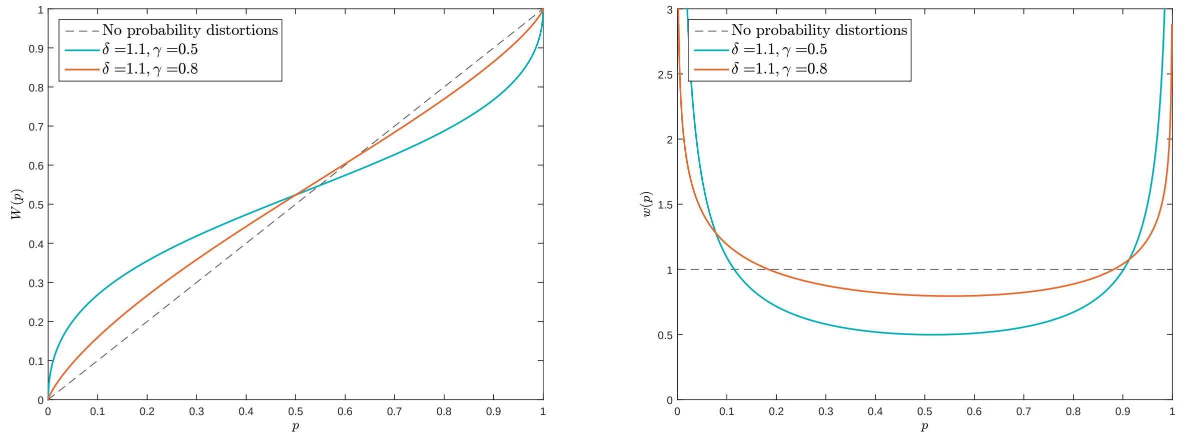
In this section, we briefly define probability weighting function and derive asset pricing equation from which we estimate the probability weighting function in Section 3.

2.1 Probability weighting

Most decision-making models assume that investors evaluate risk based on the expected utility theory, which treats payoff probabilities linearly. However, the prospect theory of Tversky and Kahneman (1992) deviates from this framework in two fundamental ways. Firstly, it considers an individual's reference point while assessing market outcomes and payoffs as gains and losses, leading to loss aversion. Secondly, it depicts how individuals distort objective probabilities of outcomes or lotteries by overweighting small probabilities and underweighting high probabilities. These violations of linearity in expectations can be captured through the risk spectrum and probability weighting function, which reflect an individual's risk attitudes and their ability to pay attention to multiple outcomes. Figure 1(a) and (b) in this context highlight the deviations from expected utility and linear probability weighting, where the dashed line corresponds to the objective probability of the expected utility theory, and positive and negative deviations indicate overweighting and underweighting.

We specify the probability weighting function of prospect theory as in Gonzalez and Wu

[2] Previous research has found correlations between certain factors and cross-sectional returns and equity premiums. For example, high past realized returns are negatively correlated with expected stock returns (Bali et al. (2011)). Stocks with high idiosyncratic skewness tend to have low expected returns (Boyer et al. (2010)). Additionally, investor sentiment can help explain expected returns (Stambaugh and Yuan (2017)).



(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 $w(p) = W'(p)$.

(1999):

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

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

which overweights the risk in the tails (Figure 1(b)).

The curvature of the probability weighting function intuitively reflects an individual's tendency to pay more attention to less probable outcomes. This results in the possibility effect, which favors risk seeking for gains and risk aversion for losses. Conversely, the certainty effect encourages risk seeking in the domain of losses and risk aversion for gains by underweighting large probabilities. Gonzalez and Wu (1999) differentiate between two key aspects of the weighting function - sensitivity and attractiveness - which govern investment behavior. Those with linear weighting function have constant sensitivity, while those with a step function are extremely sensitive around 0 and 1, and insensitive in between. Sensitivity is evident in probability distortions around the reference points of 0 and 1. Attractiveness determines the strength of overweighting, with higher elevation associated with higher risk aversion in the loss domain.

2.2 Asset pricing under probability weighting

The model is a simplified version of Brunnermeier and Sannikov (2014), while the banks operate under an expected loss constraint. 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 and losses, and as such, formulations where agents' decisions are determined solely by prospect theory should be avoided.

The model assumes a single consumption good and a single factor of production, with the only type of agent being risk-averse banks. The utility of banks is determined by consumption and a discount factor ρ

$$E\left[\int_0^\infty e^{-\rho t}\log c_t dt\right]. \tag{3}$$

Banks produce final good from capital, with linear production function

$$y_t = Ak_t, \tag{4}$$

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

$$\frac{dk_t}{k_t} = \sigma dW_t, \tag{5}$$

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

$$dn_t = Ak_t d_t + d(q_t k_t) - r_t(q_t k_t - n_t)dt - c_t dt. \tag{6}$$

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

$$\frac{dq_t}{q_t} = \mu_t^q dt + \sigma^q dW_t. \tag{7}$$

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

$$\frac{d(q_t k_t)}{q_t k_t} = (\mu_t^q + \sigma\sigma_t^q)dt + (\sigma + \sigma_t^q)dW_t. \tag{8}$$

Let $X_t \equiv q_t k_t$ denote the value of bank assets at time t, and $X_{t+\tau}$ the future value of capital at time $t+\tau$ when the capital exposure between time t and time $t+\tau$ is kept unchanged. We define market loss between the period t and $t+\tau$

$$L(t, t+\tau) \equiv X_{t+\tau} - X_t. \tag{9}$$

Since bank assets are marked to market, market gains and losses are captured by the change of the value of capital $d(q_t k_t)$. We assume that bank's borrowing is restricted by capital constraint that forces bank to hold enough capital to compute subjective expected market losses between the period t and $t+\tau$. To compute expected loss, we first define Value at Risk in as the maximum market loss that can occur with probability p

$$P(L(t,t+\tau) \geq VaR(p)) \leq p.$$

$VaR_p^{t,t+\tau}$ 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 A we present the proof for the following propositions that compute subjective expected losses.

Proposition 1.

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

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

Proposition 2. *The expected loss based on probability weighting function in (2) is*

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

It is important to note that L_W denotes subjective expected loss, which is governed by the probability weighting function. The expected utility theory is recovered when banks treat probabilities linearly and $W(p) = p$. The prospect theory enters the bank oprimization problem through capital requirement constraint - banks need to ensure that their net worth is adequate to cover subjective expected losses

$$q_t k_t L_W \leq n_t \tag{10}$$

This constraint can be enforced by investors, regulators, or banks themselves, and represents the collective perception of market losses by three agents, henceforth termed as bank's subjective expected losses. Banks choose k_t and c_t to maximize expected utility (3) subject to net worth evolution (6) and the expected loss constraint (10).

Proposition 3. *The bank optimization leads to the asset pricing equation*

$$\frac{A}{q_t} + \mu_t^q + \sigma\sigma_t^q - r_t = \frac{1}{L_W}(\sigma + \sigma_t^q)^2 + \lambda q_t L_W, \tag{11}$$

where λ is a Lagrange multiplier on the expected loss constraint (10).

The proof is in Appendix A. The Lagrange multiplier serves as an indicator to determine whether the capital requirement constraint is binding or non-binding. Upon examining equation (11), it is evident that the equity premium banks earn is equivalent to the standard risk premium in addition to the subjective expected loss premium. A positive loss premium implies that banks are averse to losses and require supplementary compensation for their expected market losses exposure. Conversely, a negative expected loss premium indicates that banks are risk-seeking in market losses.

3 Data and methodology

3.1 Capital Purchase Program Background

In response to the 2008 market downturn, the US Treasury established the Troubled Asset Relief Program (TARP) to stabilize the country's financial system. The Capital Purchase Program (CPP) was the largest and first program under TARP, which provided capital injections to liquidity-constrained financial institutions. The program involved purchasing preferred stocks and provided up to $250 billion to 707 financial institutions. Of the total funds, 81% were distributed to 17 out of 19 banks with assets above $100 billion, while the remaining funds were allocated to 690 out of 7,891 banks with assets below $100 billion. Other TARP programs included the Targeted Investment Program, Systematically Significant Failing Institutions Program, Asset Guarantee Program, and Public-Private Investment Program, which provided capital injections or guaranteed and removed troubled securities from bank balance sheets. The primary objective of the CPP was to stabilize the financial system, while the secondary objective was to improve credit availability. The program aimed to increase credit availability to the communities served by disparate banks of all sizes. 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 Econometric procedure : estimation of the probability weighting function

The main question revolves around how systemic banks, which are susceptible to insolvency risk, perceive market losses and distort probabilities.To answer this question, we jointly estimate coefficients δ and γ of the probability weighting function and the Lagrange multiplier λ from the asset pricing equation (12) by the general method of moments

$$E\left[\left(\frac{A}{q_t}+\mu_t^q+\sigma\sigma_t^q-r_t-\frac{1}{L_W}(\sigma+\sigma_t^q)^2-\lambda q_t L_W\right)Z_t\right]=0 \tag{12}$$

where Z_t are instruments.

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

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.

are provided in Table 3.

Table 2: BIGGEST BANKS DATA

Variable	Empirical counterpart	Source
Core Variables		
$\frac{A}{p_t} + \mu^q$	Holding period returns with dividends	CRSP
σ	Historical S&P volatility	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

Our study employs five Fama-French risk factors as instruments for restricted GMM, 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. Additionally, we use book-to-market factors (BM0, Lo30, and Med40) and momentum factor (MoM) interchangeably instead of MktRF. The literature on equity premium presents two distinct views on the underlying economic drivers of the equity premium or excess return. The institutional or agency view suggests that the risk-adjusted return is driven by leverage constraints, and risk should be measured using systematic risk (Frazzini and Pedersen (2014)). In contrast, the behavioral view suggests that 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, our study proposes that probability distortions capture behavioral factors separate from leverage factors.

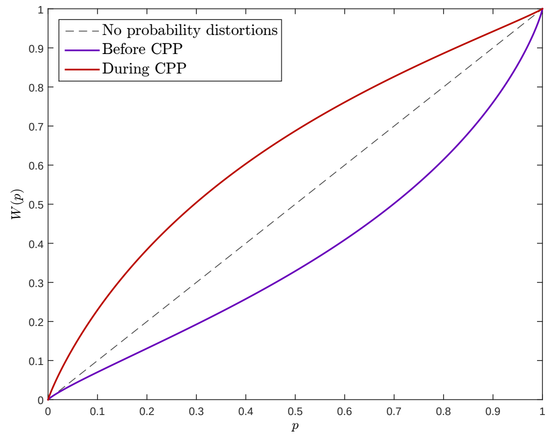
Table 3: Data Summary : Core Variables

	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

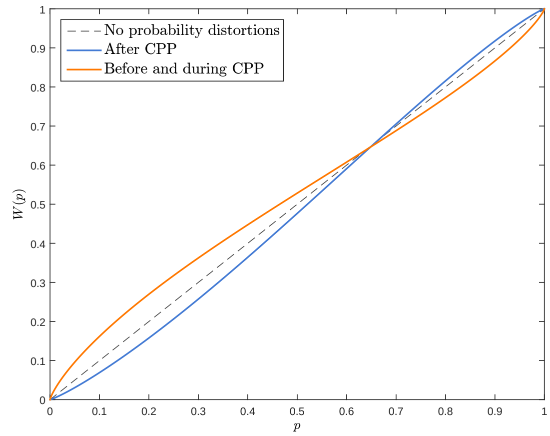
3.3 Results

Tables from 4 to 7 present the GMM estimation of parameters of probability weighting function and the Lagrange multiplier for various combinations of five Fama-French factors as instruments. In addition, Figures 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 focus is to investigate if banks consistently distort probabilities or if distortions vary across periods. Tables report banks' attractiveness to gambling δ and sensitivity to probabilities γ.

The estimates for δ and γ before the CPP recapitalization are significant at 0.485 and 0.85,



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



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

Figure 2: Estimated probability weighting functions of systemic banks. *Notes*: Figures plot the probability weighting function $W(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$ for estimated parameter values of δ and γ from column (6) in Tables 4 to 7.

respectively, whereas estimates for λ range from -0.151 to 1.52 and are insignificant. The value of δ below 1 suggests a significant underweighting of small probability market losses. In domain of losses, smaller the $\delta < 1$, the more optimistic outlook and a hopeful is the bank to avoid losses. Conversely, larger the $\delta > 1$, the more pessimistic outlook and a fearful of tail losses the bank is. The underweighting hypothesis was not rejected (p-value(λ^2)=0.000 for hypothesis $\delta = 1$). Furthermore, the reduced sensitivity to probability changes (p-value(λ^2)=0.000 for hypothesis $\gamma = 1$) even further supports the underweighting hypothesis. As for the rationale for government intervention, the positive estimates of λ in Table 4 might provide evidence that banks were experiencing difficulties in managing their liquidity. However, we cannot reject the hypothesis that large banks were sufficiently capitalized before the government intervention (p-value(λ^2)=0.665 for hypothesis $\lambda = 0$).

According to Figure 2(a) and the estimate for $\delta = 2.204$ in Table 5, banks overweighted tail market losses during the government intervention. This is suggested by the elevated probability weighting function above the 45-degree line, which implies that banks were more pessimistic and overweighted probabilities relative to objective probabilities. Moreover, the sensitivity is slightly higher as $\gamma = 0.906$ was closer to 1. 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), the estimated coefficients in column (7) of Table 5 shows that elevation and curvature remains almost unchanged, with $\delta = 2.262$ and $\gamma = 0.911$.

The combination of periods before and during the CPP gives rise to an inverse-S shape of prospect theory, as observed in the orange line in Figure 2 (b). Banks are most responsive around two reference points - 0 (impossibility) and 1 (certainty) - while remaining almost unresponsive to the middle region. Surprisingly, banks' average preferences reveal theoretically

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

The tble reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier λ 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. Corresponding Newey and West (1994) standard errors are shown in parentheses. The sample period is from January 2nd, 2007, through June 30th, 2008.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	0.485***	0.485***	0.484***	0.485***	0.485***	0.485***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
γ	0.850***	0.850***	0.850***	0.850***	0.850***	0.850***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
λ	0.131	0.146	−0.151	0.152	0.120	0.122
	(0.286)	(0.303)	(1.238)	(0.328)	(0.282)	(0.281)
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	0.92	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 λ 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. Corresponding Newey and West (1994) standard errors are shown 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	2.550***	2.041***	2.460***	2.196***	2.080***	2.204***	2.262***
	(0.022)	(0.046)	(0.023)	(0.027)	(0.009)	(0.003)	(0.012)
γ	0.991***	0.892***	0.784***	0.867***	0.842***	0.906***	0.911***
	(0.003)	(0.015)	(0.007)	(0.009)	(0.004)	(0.000)	(0.003)
λ	0.084	0.139	−0.035	0.059	−0.041	0.072	0.037
	(1.804)	(0.447)	(0.074)	(0.449)	(0.068)	(0.320)	(0.185)
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

meaningful values found in laboratory settings. Our estimates of δ and γ are 1.124 and 0.8, respectively (Table 6, column (6)), which are similar to those found in literature that applies prospect theory in laboratory settings. For instance, Etchart-Vincent (2004) find $\delta = 1.1$ and $\gamma = 0.84$ in the domain of losses, while Abdellaoui et al. (2005) reports more pessimistic responses ($\delta = 1.35$) and similar sensitivity ($\gamma = 0.84$). In comparison to our results, Fehr-Duda et al. (2006) explore gender-specific probability weighting in abstract and context environments and find that participants discriminate probabilities less than financial institutions ($\gamma = 0.57$ for men and $\gamma = 0.47$ for women) and exhibit a similar degree of pessimism ($\delta = 1.14$ for men and $\delta = 1.06$ for women in contextual settings and $\delta = 1.1$ for men and $\delta = 1.10$ for women in abstract gamble formulations).

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 λ 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. Corresponding Newey and West (1994) standard errors are shown in parentheses. The sample period is from January 2nd, 2007, through December 26th, 2008.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	1.132***	1.168***	1.096***	1.103***	1.242***	1.124***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
γ	0.850***	0.938***	0.870***	0.744***	0.750***	0.800***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
λ	0.008	−0.058	0.041	0.021	−0.020	−0.033
	(0.074)	(0.289)	(0.128)	(0.034)	(0.094)	(0.046)
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	0.91	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

The probability weighting function takes an S-shape after the CPP, indicating an optimistic psychological response towards the possibility of tail market losses. The estimated values of δ and γ after recapitalization, as suggested by Table 7, are 0.907 and 1.135, respectively. $\gamma > 1$ suggests that banks pay substantial attention to changes in loss probabilities, rather than being complacent. While most studies report an inverse-S shaped weighting function, some studies do find a sensitivity parameter larger than one, as reported by Goeree et al. (2002); Van de Kuilen and Wakker (2011).

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 λ 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. Corresponding Newey and West (1994) standard errors are shown in parentheses. The sample period is from January 2nd, 2010, through December 31st, 2010.

	Asset Pricing Equation					
	(1)	(2)	(3)	(4)	(5)	(6)
δ	0.874***	0.842***	0.898***	0.702***	0.832***	0.907***
	(0.020)	(0.001)	(0.007)	(0.015)	(0.009)	(0.006)
γ	1.371***	1.156***	1.147***	1.258***	1.110***	1.135***
	(0.023)	(0.001)	(0.007)	(0.011)	(0.006)	(0.002)
λ	−0.320	−0.521	−0.203	−0.053	0.226	0.130
	(0.307)	(0.360)	(0.252)	(0.105)	(0.167)	(0.239)
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	0.93	0.94	0.89	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

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 λ 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. Corresponding Newey and West (1994) standard errors are shown 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	0.539***	1.038***	2.367***	0.843***
	(0.001)	(0.001)	(0.009)	(0.001)
γ	0.890***	0.920***	0.798***	1.156***
	(0.000)	(0.000)	(0.003)	(0.000)
λ	−0.064	0.133**	0.002	−0.614**
	(0.401)	(0.059)	(0.078)	(0.290)
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	

It is worth noting that the estimation of GMM with Lo30 suggests that banks were risk-averse and constrained in losses before and during the crisis. The resulting value of $\lambda = 0.133$ rejects the hypothesis of unconstrained banks at a 5% level (p-value(λ^2) = 0.02565 for hypothesis $\lambda = 0$). On the other hand, the use of Med40 instrument indicates that banks become unconstrained after they have been recapitalized, as $\lambda = -0.614 < 0$ (p-value(λ^2) = 0.03435 for hypothesis $\lambda = 0$). In this context, book-to-market equity emerges as a stronger predictor of the constrainedness of systemic banks compared to the overall market return.

To summarize, the results reveal a state-dependent or time-dependent probability weighting: convex (underweighting) before the CPP, concave (overweighting) during the CPP, inverted S-shaped before and during the CPP, and S-shaped after the CPP. The results remain consistent when book-to-market or momentum factors are included as instruments instead of the market factor MktRF. The findings are summarized in Table 8 and Table 11 in Appendix B. Figure 4 in Appendix B plots the estimated probability weighting functions with book-to-market and momentum factors, which are quantitatively similar to the results of the baseline GMM.

3.4 Discussion

Our model assumes that banks are rational agents who maximize expected utility while assessing subjective expected losses using probability weighting. However, empirical evidence reveals nonlinear probability weighting that directly violates the expected utility. Additionally, our analysis uncovers a positive Lagrange multiplier before and during government intervention and a negative one post-recapitalization. This suggests risk aversion before and risk-seeking after government intervention, contradicting EUT's assumption of consistent risk aversion. Moreover, our findings cast doubt on the consistency of the inverted S-curve of prospect theory across various informational contexts, particularly in explaining the transition from overweighting to underweighting of small probability losses. Based on this evidence, prospect theory remains valid in the absence of government intervention, leading us to conclude that a state-dependent probability weighting function offers a more comprehensive explanation for our results.

The observed shift in risk attitudes among banks following recapitalization after significant losses may be due to prior losses. Previous research has shown that agents tend to become either more risk-seeking (Shefrin and Statman (1985);Andrade and Iyer (2009); Langer and Weber (2008)) or more risk-averse (Andrade and Iyer (2009); Langer and Weber (2008);Barberis et al. (2001); Dillenberger and Rozen (2015)) after a loss. However, recent studies have indicated that investors may respond differently to realized losses than paper losses (Imas (2016)). Recapitalization might encourage banks to perceive realized losses as paper losses. Consider the impact of government intervention in the expected loss constraint, specifically in the case of bank recapitalization. Recall the constraint on expected loss states that $q_t k_t L_W \leq n_t$ without government intervention. But what happens when the government steps in to recapitalize banks? Recapitalization can occur through either increasing equity or reducing losses, with two channels at play: institutional and behavioral. In the institutional channel, recapitalization increases equity without altering the reference point for losses ($q_t k_t L_W \leq n_t + G$), resulting in a reduction of the Lagrange multiplier post-recapitalization. However, the multiplier remains non-negative, with $0 \leq \lambda_G < \lambda$. The probability weighting function should remain constant during and after recapitalization. The behavioral channel involves a shift in the reference point, and the constraint becomes $q_t k_t L_W - G \leq n_t$. Recapitalization can reduce losses at any range of the market loss distribution, leading to a shift in risk-seeking behavior and underweighting small probability losses. The shift is reflected in the probability weighting function, which becomes state-dependent $L_W(G)$, and a negative Lagrange multiplier, $\lambda_G < 0$. These findings have significant implications, with banks potentially underestimating their ability to avoid losses after recapitalization and engaging in risk-seeking behavior.

Recent studies argue that context-dependent probability weighting function may indicate state dependence, delay dependence, or shifting reference points (Fehr-Duda and Epper (2011)). Abdellaoui et al. (2011) finds that the probability weights in the domain of gains are sensitive to the resolution of uncertainty. Their experiment confirms the inverse S-shape for non-delayed lotteries, which are resolved and paid out in the present versus the future. However, introducing a time delay generates the probability weighting function with more weighting of small probability gains. Epper and Fehr-Duda (2017) propose that the way people weigh probabilities depends on the timing of consequences and uncertainty resolution. Their model suggests that individuals' willingness to take risks is influenced by how long they have to wait and how certain they are about the outcome. When time is not a factor, people tend to overestimate the likelihood of rare negative events occurring soon but underestimate the probability of such events happening in the distant future. However, if the outcome is uncertain and will take time to unfold, individuals tend to overestimate the chances of negative rare events happening. Conversely, if they know when the outcome will be revealed, they tend to underestimate the likelihood of negative events. According to the salience theory proposed by Bordalo et al. (2013), shifting the reference points is another explanation for context-dependent probability weighting. When market gains are salient, investors tend to focus their attention on positive market outcomes, leading to the underweighting of losses and the overweighting of gains. Conversely, investors are more likely to overweight losses when abnormal negative return realizations occur. The concave weighting function may arise when market gains are salient, and banks perceive equity to be sufficient to absorb potential losses, while the convex weighting function may reflect banks' belief in the inadequacy of equity buffer to cover losses.

4 Economic drivers of probability distortions

Our further investigation aims to explore why banks tend to overweight or underweight tail losses in their decision-making and examine the economic factors that contribute to probability distortions. We start by differentiating subjective and objective losses

$$L_{KT} - E(L) = \mathrm{e}^{(\mu^q + \sigma\sigma^q)\tau} \left(1 - \underbrace{\frac{\delta\gamma(\Phi(\sigma+\sigma^q)(1-\Phi(\sigma+\sigma^q)))^{\gamma-1}}{(\delta\Phi(\sigma+\sigma^q)^\gamma + (1-\Phi(\sigma+\sigma^q))^\gamma)^2}}_{\text{Probability distortion}} \right). \tag{13}$$

The difference between subjective and objective losses can be attributed to probability weighting or market conditions. Probability distortions can be seen in Figure 3, where zero thresholds indicate that subjective expectations of losses match objective losses. Banks systematically overweight losses during the CPP, but underweight them afterwards (as shown in Figures 3(c) and (d)). Additionally, probability distortions shifted from right to left skewness before and after recapitalization.

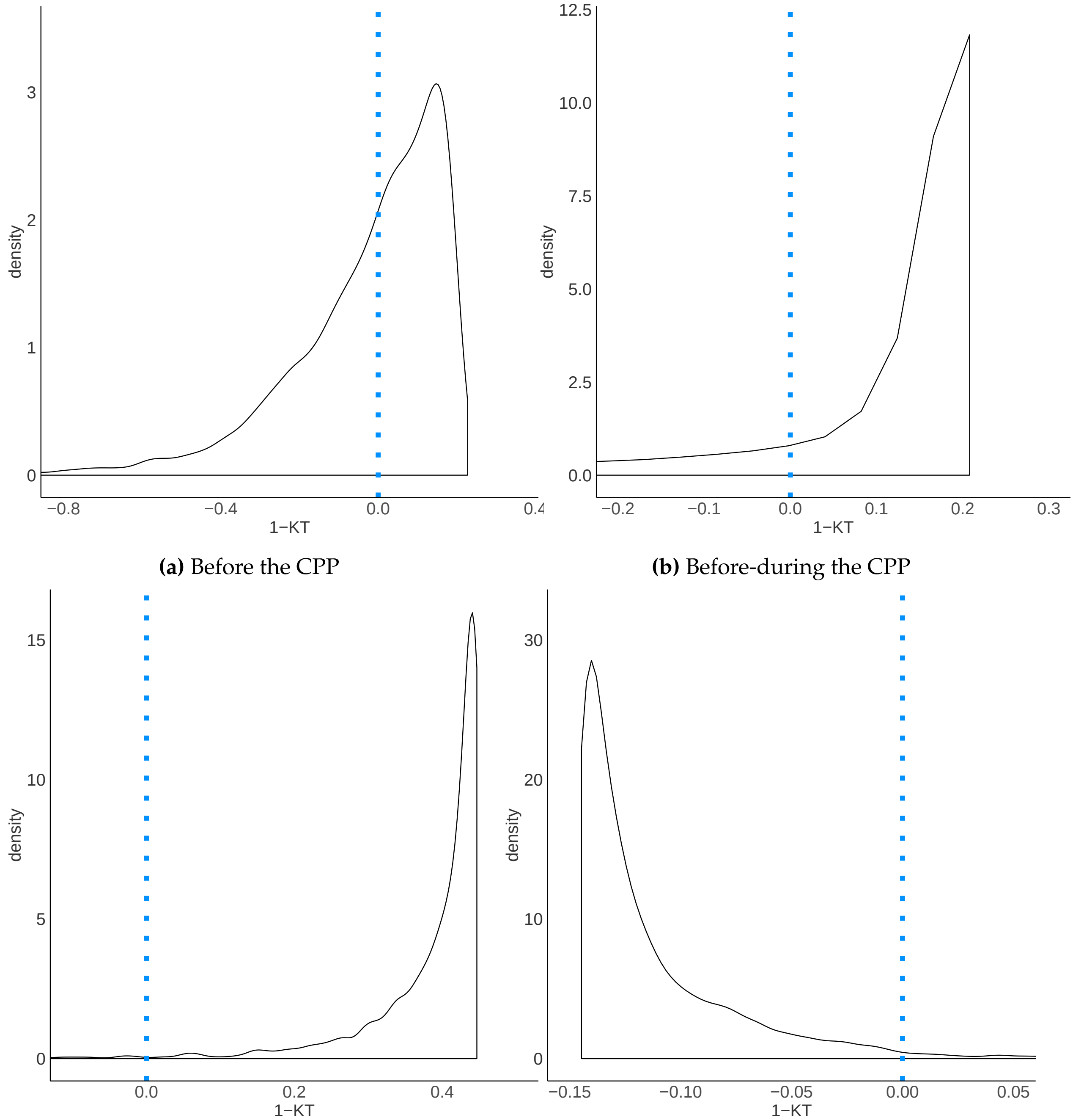
Further analysis aims to identify the factors that contribute to the gap between subjective and objective performance evaluation. To achieve this, we conduct fixed effect regressions with variables related to uncertainty resolution, reference point, state dependence, and investor sentiment. It is worth noting that, except for uncertainty resolution, these variables have been found to be predictors of excess stock returns and equity premiums in previous literature.[3] The resolution of uncertainty is especially important for systemic banks, as they need to consider the timing and probability of tail losses and government capital injections. To proxy for policy-related economic uncertainty and equity market uncertainty, we follow the methodology proposed by Baker et al. (2016) . Specifically, we use the Index of Equity Market Uncertainty (EMU) and the index of policy-related Economic Uncertainty (EPU), which are constructed based on newspaper coverage and articles related to uncertainty.[4] We use two types of risk-neutral default probabilities from Nagel and Purnanandam (2020) to proxy for bank-specific probability of tail losses. The first type assumes that bank equity payoffs resemble a put option on bank assets with limited upside potential, in contrast to the unlimited upside potential assumed by Merton (1974)'s default probabilities where a equity payoff is a call option on assets.[5] To account for reference point dependence and change from losses to gains, we include 15% tail return realizations over the past 22 days (MAX).

State-dependent factors that affect asset returns include idiosyncratic volatility, market volatility, market beta, skewness, co-skewness, prior tail losses (historical VAR), and liquidity. To estimate betas, we use rolling regressions of excess returns on market excess returns over 22 trading days. To mitigate the impact of outliers, we followFrazzini and Pedersen (2014) and shrink the time series beta estimates toward the cross-sectional mean of 1 using a scaling factor of 0.6. We compute conditional skewness following Harvey and Siddique (2000) as the covariance between the excess return of bank asset and the squared excess return on the market. Market beta and co-skewness are obtained from rolling 22 days window regressions. To

[3]

[4]The EPU index includes terms related to monetary, fiscal, and regulatory policy, while the EMU index includes stock market-related terms. Both indexes can be accessed at https://www.policyuncertainty.com/.

[5]To obtain daily frequency default probabilities from Nagel and Purnanandam (2020), we use linear interpolation from quarterly data or disaggregate quarterly series using Chow-Lin maximum likelihood method with equity price as the high-frequency indicator. It's worth noting that Nagel and Purnanandam (2020)'s sample covers 37 out of 39 banks that we consider.



(a) Before the CPP **(b)** Before-during the CPP

(c) During the CPP **(d)** After the CPP

Figure 3: The wedge between subjective and objective losses

measure liquidity, we use funding conditions represented by the TED spread and corporate bond spread, as well as Amihud (2002) measure of market liquidity, which captures market illiquidity by computing the average daily illiquidity of a security over 22 trading days.

Lastly, we examine the relationship between investor sentiment and probability distortions using three variables. We include two mispricing factors proposed by Stambaugh and Yuan (2017). The first factor, MGMT, includes net stock issues, composite equity issues, net operating assets, asset growth, investment to assets, and accruals, which are somewhat directly controllable by a firm's management. The second factor, PERF, includes distress, O-score, momentum, gross profitability, and return on assets, which are linked to a firm's performance and less directly controllable by management. The third variable, betting against beta (BAB) factor proposed by Frazzini and Pedersen (2014), proxies for the spread between underpriced and overpriced stocks, and captures the degree of market-wide mispricing.

4.1 Results : fixed-effects regressions

The estimates for the effects of uncertainty resolution, reference point, state dependence, and investor sentiment on probability distortions are detailed in Table 9. Additionally, Table 10 provides a summary of the influence of default probabilities on distortions. Our analysis includes six Fama-French factors as additional controls, namely market (MktRF), size (SMB), value (HML), investment (CMA), profitability (RMW), and momentum (MoM), in all regressions.

According to the VaR estimates in column (1), a 1% increase in prior tail losses results in a 0.06% increase in overweighting of small probabilities. Conversely, prior gains have a reducing effect on overweighting. This is evidenced by the MAX coefficient in column (3), which shows a decline of approximately 0.1% when banks experience a 1% increase in extreme positive returns. Variations in idiosyncratic and systematic skewness elicit opposite effects. As skewness is often associated with fear or hope, a rise skewness elicits hope and less overweighting. However, systematic skewness (co-skewness) positively correlates with overweighting. Similar results hold for volatilities. If bank-specific volatility increases by 1%, overweighting decreases by 1.45%. However, if market volatility or beta increases by 1%, overweighting only rises by 0.25%. The second column of Table 9 demonstrates a negative correlation between the level of the TED spread and corporate bond spread with overweighting. Specifically, an increase of 1% in the interbank borrowing rate results in a decrease of approximately 0.3% in overweighting. Similarly, tight funding conditions in the corporate bond market result in a 0.118% reduction in overweighting. The response of banks to increasing market illiquidity is only a 0.045% decline in overweighting. The TED spread is a metric used to evaluate the degree of funding constraints and liquidity shortage in financial markets. A negative correlation in this spread indicates that the major banks tend to decrease overweighting in response to liquidity shortage.

Column (3) indicates that the estimated coefficients for the BAB spread and mispricing factors related to banks' management(MGMT) are positive but not statistically significant. However, performance has a positive impact on overweighting. The estimated coefficient of 0.097 is possible absorbing the distress component of the PERF factor. This implies that distressed banks and those with a high likelihood of going bankrupt soon (O-score variable) tend to overweight small probabilities more.

It is important to note that default probabilities and government policy uncertainty have a significant impact on probability distortions. The results of Table 10 indicate that a 1% increase in default probabilities leads to a 20-24% increase in overweighting. On the other hand, high policy uncertainty is associated with less overweighting, while increasing policy uncertainty

Table 9: Determinants of probability distortion

The table presents the results from fixed-effects time-series regressions. The left-hand side variable is the probability distortion. Explanatory variables include idiosyncratic skewness, market beta, prior gains (MAX), and prior 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 EMU 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).

	$L_W - E(L)$							
	before and during the CPP				after the CPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
volatility	−1.457***				0.214***			
	(0.151)				(0.002)			
volatility S&P 500	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***				0.142***		
		(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)				−0.136***				0.007***
				(0.017)				(0.002)
Δlog(EMU)				0.059***				−0.005***
				(0.014)				(0.002)
log(EPU)				−0.224***				−0.009**
				(0.027)				(0.004)
Δlog(EPU)				0.127***				0.006
				(0.022)				(0.005)
Observations	15,890	15,489	15,890	16,625	9,247	8,966	9,249	9,210
R^2	0.585	0.216	0.212	0.157	0.933	0.084	0.112	0.015

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All standard errors are based on the heteroscedasticity-consistent standard errors of Arellano (1987).

Table 10: Determinants of probability distortions, default probabilities

The table presents the results from fixed-effects time-series regressions. The left-hand side variable is the probability distortion. Explanatory variables include default probabilities of Nagel and Purnanandam (2020) that are either linearly interpolated from quarterly data (columns 1-2), or interpolated using Chow-Lin maximum likelihood method with equity price as an indicator variable (columns 3-4). When calculating default probabilities, Nagel and Purnanandam (2020) assume that bank equity payoffs resemble a put option (PD and PD_{Chow}), or a call option(PD_{Merton} and $PD_{Merton-Chow}$). 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).

	$L_W - E(L)$							
	before and during the CPP				after the CPP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PD	-1.958^{***}				0.090^{***}			
	(0.190)				(0.026)			
Δ PD	20.917^{**}				6.794^{***}			
	(9.338)				(0.692)			
PD_{Merton}		-1.378^{***}				0.021		
		(0.135)				(0.013)		
ΔPD_{Merton}		24.307^{***}				4.457^{***}		
		(7.655)				(0.416)		
PD_{Chow}			-1.837^{***}				0.010	
			(0.180)				(0.016)	
Δ PD_{Chow}			1.887				0.138	
			(1.308)				(0.198)	
$PD_{Merton-Chow}$				-1.368^{***}				0.007
				(0.127)				(0.007)
$\Delta PD_{Merton-Chow}$				1.153				0.001
				(1.197)				(0.161)
Observations	14,623	14,623	15,625	15,625	6,204	6,204	8,708	8,708
R^2	0.156	0.181	0.143	0.177	0.031	0.023	0.005	0.005
Note:						*p<0.1; **p<0.05; ***p<0.01		

leads to more overweighting. 1 percent increase in policy uncertainty results in a 0.12 percent rise in overweighting. Moreover, policy uncertainty plays a more crucial role in probability distortions than uncertainty in equity markets. These findings suggest that monetary, fiscal, and regulatory policy uncertainty have a significant economic impact on how major financial institutions perceive and evaluate losses. If the government communicates its decision clearly and is firm in its stance, this may reassure banks about government backing and reduce overweighting. However, if the government is reluctant to bail out banks, this lack of transparency may push banks to respond to tail market losses by overreacting.

According to Table 9, the Ted spread, prior gains, and bank-specific and market volatility all contribute to underweighting of small probabilities after recapitalization. The same holds true for default probabilities, as indicated by the positive estimates in column (5)-(6) in Table 10. The effects of other variables such as policy uncertainty or prior losses, are muted or insignificant compared to the period after the government recapitalization program.

In summary, our findings suggest that factors including market volatility, beta, systematic skewness, mispricing, default risk, policy and market uncertainty exacerbate the overweighting of large banks before and during the recapitalization program. On the other hand, interbank funding illiquidity, bank-specific volatility, and prior have a dampening effect.

5 Conclusion

The study of decision-making theories under risk has been an active field of research in behavioral finance. This paper aims to test the concept of probability weighting from prospect theory in the context of the financial market, specifically in relation to systemically important financial institutions

The paper identifies the context-dependent probability weighting function of large banks that were recapitalized under the Capital Purchase Program. The function shows a concave, convex, concave-convex, and convex-concave pattern during different periods. Before recapitalization, the largest banks tend to underweight the probability of tail losses. However, during market turmoil and amid the CPP recapitalization, banks overweight the likelihood of the worst possible scenario. 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 results also reveal that banks are risk-averse in losses before and during government intervention and risk-seeking afterward.

Furthermore, the paper demonstrates that market volatility, skewness, mispricing, interbank funding liquidity, policy uncertainty, and default risk are the underlying mechanisms for the overweighting and underweighting of tail events. In conclusion, the results of the study highlight the significance of probability weighting in explaining the risk perceptions of systemic financial institutions. Generalizing the results beyond large and recapitalized banks is a promising direction for future research.

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A Proofs

Proof of Proposition 1. Recall that we defined market losses as $X_t - X_{t+\tau}$ and $VaR(p)$ as

$$VaR(p) = \inf\{L \geq 0 : P(X_t - X_{t+\tau} \geq L) \leq p\} = (Q^p_{t,t+\tau})^-,$$

where

$$Q^p_{t,t+\tau} = \sup\{L \in \mathbb{R} : P(X_{t+\tau} - X_t \leq L) \leq p\}$$

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

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

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

$$\begin{aligned}
&P(X_{t+\tau} - X_t \leq L) \leq p\\
&\Phi\left(\frac{\log(1 + \frac{L}{X_t}) - (\mu^q_t + \sigma\sigma^q_t - \frac{1}{2}(\sigma + \sigma^q_t)^2)\tau}{(\sigma + \sigma^q_t)\sqrt{\tau}}\right) \leq p\\
&L \leq X_t\left(\exp\left((\mu^q_t + \sigma\sigma^q_t - \frac{1}{2}(\sigma + \sigma^q_t)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma^q_t)\sqrt{\tau}\right) - 1\right)
\end{aligned}$$

which implies

$$Q^p_{t,t+\tau} = X_t\left(\exp\left((\mu^q_t + \sigma\sigma^q_t - \frac{1}{2}(\sigma + \sigma^q_t)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma^q_t)\sqrt{\tau}\right) - 1\right)$$

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

$$VaR(p) = q_t k_t\left(1 - \exp((\mu^q_t + \sigma\sigma^q_t - \frac{1}{2}(\sigma + \sigma^q_t)^2)\tau + \Phi^{-1}(p)(\sigma + \sigma^q_t)\sqrt{\tau})\right).$$

□

PROOF OF PROPOSITION 2. We use Laplace's method to prove the expression for EL_{KT}. In general case, Laplace's method determines the leading-order behavior of the integral

$$I(\lambda) = \int_a^b f(x) e^{-\alpha g(x)} dx. \tag{14}$$

We assume that integral converges for α 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

$$I(\alpha) \approx e^{-\alpha g(c)} f(c) \sqrt{\frac{2\pi}{\alpha g''(c)}} \tag{15}$$

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.

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

In our case, $\alpha = -1$, $f(x) = \dfrac{\delta\gamma(\Phi(x)(1-\Phi(x)))^{\gamma-1}}{(\delta\Phi(x)^\gamma + (1-\Phi(x))^\gamma)^2}$, $g(x) = e^{\frac{(x-(\sigma+\sigma_t^q)\sqrt{\tau})^2}{2}}$. 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 EL_{KT}. □

PROOF OF PROPOSITION 3. Let us now solve for bank maximization problem. Banks' *Hamilton-Jakobi-Bellman* equation is

$$\rho V(n_t) = \max_{c_t, k_t} \quad \log c_t + V'(n_t)[Ak_t + r_t n_t + q_t k_t(\mu_t^q + \sigma\sigma_t^q - r_t) - c_t] + \frac{1}{2}V''(n)(\sigma + \sigma_t^q)^2 q_t^2 k_t^2 + \lambda\left[n_t - q_t k_t L_W\right]. \tag{16}$$

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

$$\frac{1}{c_t} = V'(n_t) \tag{17}$$

$$\frac{A}{q_t} + \mu_t^q + \sigma\sigma_t^q = r_t + \frac{-V''(n_t)(\sigma + \sigma_t^q)^2 q_t k_t + \lambda q_t L_W}{V'(n_t)} \tag{18}$$

$$\lambda(n_t - q_t k_t L_W) = 0. \tag{19}$$

In order to obtain asset pricing equation (18) we need to solve for banks' optimal consumption from Euler equation by using the method of matching drifts. Let $\chi = V'(n)$ represent banks' stochastic discount factor and let it follow Brownian motion

$$d\chi = \mu^{\chi}\chi dt + \sigma^{\chi}\chi dW_t$$

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

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

$$\sigma^{\chi}\chi = V''(n)(\sigma + \sigma^q)qk$$

The envelope condition of banks is

$$\begin{aligned}
\rho V'(n) &= \left(\log c - V'(n)c\right)' + \left(V'(n)\left[A\frac{n}{qL_W} + r_t n + \frac{n}{L_W}(\mu^q + \sigma\sigma^q - r_t)\right]\right)' \\
&\quad + \frac{1}{2}\left[V''(n)(\sigma + \sigma^q)^2\frac{n^2}{L_W^2}\right]' + \lambda'(n)\left[n - qkL_W\right] + \lambda(n)\left[n - qkL_W(n)\right]' \\
&= \left(\frac{1}{c}c'(n) - V'(n)c(n) - V''(n)c\right) + V''(n)\left[A\frac{n}{qL_W} + r_t n + \frac{n}{L_W}(\mu^q + \sigma\sigma^q - r_t)\right] \\
&\quad + V'(n)\left[r_t + \frac{1}{L_W}(A + \mu^q + \sigma\sigma^q - r_t)\right] + V''(n)\left[(\sigma + \sigma^q)^2\frac{n}{L_W^2}\right] \\
&\quad + \frac{1}{2}\left[V'''(n)(\sigma + \sigma^q)^2\frac{n^2}{L_W^2}\right]
\end{aligned}$$

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

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

Therefore, the stochastic discount factor of intermediaries evolves as

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

giving us the expression for the drift of the SDF

$$\mu^{\chi} = \rho - r_t - \frac{1}{L_W}(\frac{A}{q} + \mu^q + \sigma\sigma^q - r_t) - (\sigma + \sigma^q)\frac{\sigma^{\chi}}{L_W}. \tag{20}$$

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

$$\chi\left(A + q(\mu^q + \sigma\sigma^q - r_t)\right) + (\sigma + \sigma^q)\sigma^{\chi}\chi q - \lambda q L_W = 0. \tag{21}$$

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

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

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

$$\mu^c = -\mu^{\chi} + (\sigma^{\chi})^2, \quad \sigma^c = -\sigma^{\chi}. \tag{22}$$

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

$$\mu^c c = c'(n)[Ak + r_t n + qk(\mu^q + \sigma\sigma^q - r_t) - c] + \frac{1}{2}c''(n)(\sigma + \sigma^q)^2 p^2 k^2, \tag{23}$$

$$\sigma^c c = c'(n)(\sigma + \sigma^q)qk = c'(n)(\sigma + \sigma^q)\frac{n}{L_W}. \tag{24}$$

Now we match consumption drifts using (23),(24),(22),(21), and (20) we get

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

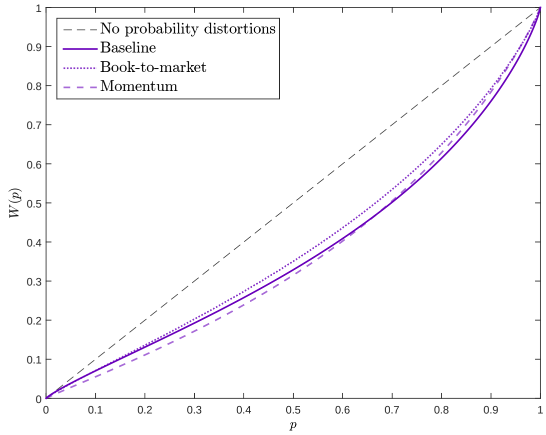
Guessing a linear consumption rule we get $c(n) = An + F$ and substituting it in matching drifts we get $c(n) = \rho n$. Using Euler equation (17), we have $V'(n) = \dfrac{1}{\rho n}$, and $V''(n) = -\dfrac{1}{\rho n^2}$. Finally, plugging back expressions for $V'(n), V''(n)$ into asset pricing equation (18), we obtain the asset pricing equation from the main text, which concludes the proof. □

B Additional Tables and Figures

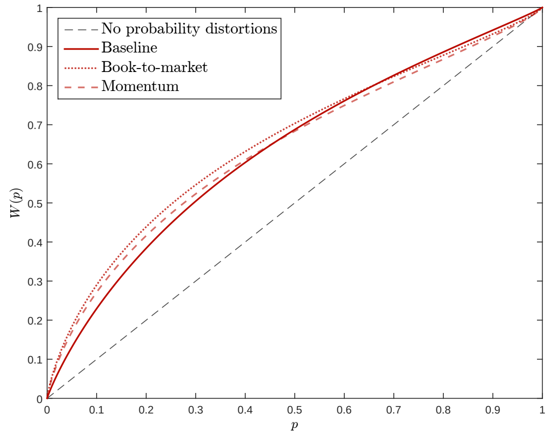
Table 11: GMM estimation of Kahneman-Tversky's probability weighting function with momentum instrument

This table reports the results of restricted GMM estimation of coefficients δ and γ of probability weighting function and the Lagrange multiplier λ 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. Corresponding Newey and West (1994) standard errors are shown 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).

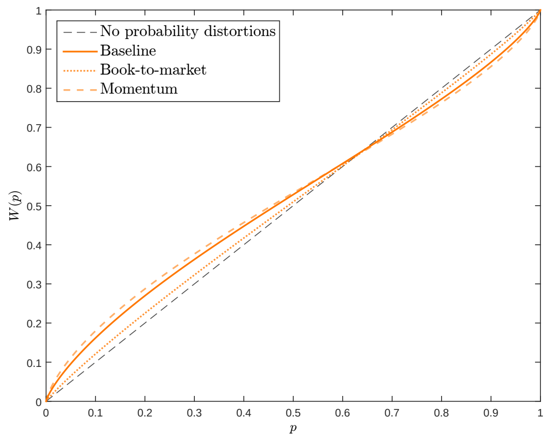
	Asset Pricing Equation			
	before CPP	before-during CPP	during CPP	after CPP
δ	0.459***	1.138***	2.156***	0.929***
	(0.002)	(0.001)	(0.013)	(0.001)
γ	0.944***	0.749***	0.803***	1.138***
	(0.001)	(0.001)	(0.005)	(0.001)
λ	−0.076	−0.010	0.143	−0.060
	(0.065)	(0.013)	(0.116)	(0.552)
SMB	Y	Y	Y	Y
HML	Y	Y	Y	Y
RMW	Y	Y	Y	Y
CMA	Y	Y	Y	Y
MoM	Y	Y	Y	Y
J-test p-value	0.92	0.95	0.98	0.92
Observations	12,188	16,670	3,013	9,249
Note:				*p<0.1; **p<0.05; ***p<0.01



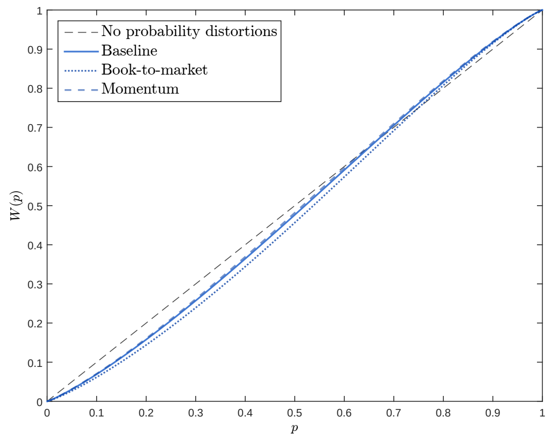
(a) Before the CPP



(b) During the CPP



(c) Before and during the CPP



(d) After the CPP

Figure 4: 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.