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Did capital infusions enhance bank recovery from the great recession? ☆

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ABSTRACT

This paper investigates the long-run recovery experience of US banks that received capital infusions under the Capital Purchase Program (CPP), a part of the Troubled Asset Relief Program (TARP). Based on a dynamic recovery model, our results show that recovering CPP banks tended to be in better financial condition than other CPP banks. Long-run event study analyses of common stock prices reveal that, in the quarter after repayment of TARP funds, CPP banks experienced economically large and significant buy-and-hold wealth gains of 14%, equivalent to approximately $329 billion. We conclude that TARP was successful in fostering bank financial and stock price recovery.

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1. Introduction

> “I certainly think that the TARP has mostly served its purpose and that it’s time to start thinking about how we are going to unwind that program … many banks are paying back the TARP and a lot of the money that was put out is now coming back to the Treasury”.

Chairman Ben Bernanke in a Senate Banking Committee hearing (December 3rd, 2009).

Unprecedented failures occurred in 2008 among large financial institutions engaged in the securitization of home loans. Bear Stearns and Merrill Lynch merged with commercial banks at fire-sale prices, Lehman Brothers was liquidated, government-sponsored mortgage lenders Fannie Mae and Freddie Mac were nationalized, and a number of megabanks became insolvent. Panic in financial markets caused collapses of capital asset prices on a global scale. In an effort to restore stability and liquidity to the financial system, the US government passed the Emergency Economic Stabilization Act on October 3, 2008 to mitigate systemic risk. Under this Act, the Troubled Asset Relief Program (TARP) provided the US Treasury with $700 billion to bail out failing institutions[4] and prevent a repeat of the Great Depression banking collapse.[5]

Taking advantage of TARP funds, US Treasury Secretary Paulson on October 14, 2008 opened the Capital Purchase Program (CPP)[6] designed to inject cash into banks in exchange for preferred stock

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[4] Although the Act stated that only relatively strong institutions would be eligible for TARP funding, the program was later aimed at rescuing troubled banks and automobile companies. See Ghosh and Mohamed (2010) and Broome (2011) for excellent overviews of TARP.

[5] About one-half of US banks (or approximately 15,000 banks) closed their doors in the Great Depression. Studies by Bernanke (1983) and Anari et al. (2005) show that credit contractions associated with large numbers of bank failures exacerbated the depth and duration of the economic downturn in the Depression years. See also Shimizu (2006) on efforts by the Japanese government from 1999 to 2001 to stabilize the economy by injecting capital into banks and requiring them to expand bank credit under the Business Revitalization Plan during the financial crisis at that time.

[6] TARP resources were committed by the Treasury to different programs as follows: Capital Purchase Programs (CPP) – $250 billion, Public–Private Investment Program (PPIP) – $100 billion, Term Asset-Backed Securities Loan Facility (TALF) – $100 billion, Systematically Significant Failing Institutions (AIG) – $70 billion, etc. (see the Treasury report to Congress, June 10, 2011).

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and warrants.[7] After implementing stress tests to gauge impending losses in large institutions, regulatory capital requirements were imposed by infusing capital to meet minimum common equity levels after projected losses. Over the course of the program, a total of 707 CPP institutions received $205 billion in TARP funds. About $190 billion was paid out to large banks with more than $10 billion in assets. Hence, TARP funds were primarily intended to keep large banks afloat until the economy revived. Implicit in this strategy was the presumption that solvent institutions would act prudently to manage their financial condition, recover from their losses, and repay TARP funds within a reasonable period of time. As of June 1, 2011, 130 institutions had repaid $180 billion with remaining balances outstanding at small bank participants.[8]

In this paper we examine the recovery experience of CPP banks receiving TARP funds. We define the recovery period as the time span from receipt to later repayment of TARP funds by participating banks. Small banks with less than $500 million in assets are excluded from our analyses due to the lack of requisite accounting and financial data. We contribute to the growing TARP literature by providing evidence on the following research questions: What are the determinants of financial condition recovery among CPP banks that repaid TARP funds compared to other CPP banks? Can we use such information to predict future CPP bank recoveries? Did participating banks experience stock wealth gains during or after the period of repayment? Is there a relationship between financial condition and stock price recovery? Are there policy implications that would be useful to regulators and other government officials in terms of effectively managing systemic bank risk?

Our empirical analyses investigate CPP banks' health from two perspectives: (1) we develop a dynamic recovery model to capture the time series characteristics of CPP banks' financial recovery and (2) we perform a long-run event study using CPP banks' common stock prices to measure wealth effects over time. Our dynamic recovery model utilizes quarterly bank holding company data from December 2007 to December 2010 to identify the determinants of bank recovery. Financial health is proxied in terms of the recovery probability of repaying CPP banks relative to nonrepaying CPP banks. Our main contribution in this respect is to document the determinants of changes in financial health among CPP banks after the implementation of TARP. In brief, our results show that recovering CPP banks that repaid TARP obligations tended to have stronger overall financial condition, as reflected in higher capital, asset quality, profits, dividends, liquidity, and size, than nonrecovering CPP banks. Further out-of-sample tests based on forecasted probabilities of bank recovery derived in the present paper support the reliability of the dynamic recovery model. These new forecasted probabilities contribute to the emerging dynamic hazard literature (e.g., see Shumway, 2001; Duffie et al., 2007; Duffie et al., 2009) by enabling bank regulators, academic researchers, and others to more readily utilize dynamic models as early warning systems (EWSs).

Our long-run event study investigates CPP common stock reactions in the following well-defined event windows: before the receipt of TARP funds, within the interim from receipt to later repayment of TARP funds, and after repayment. We use a variety of event study methodologies. Stock prices should reflect the full information effects of capital infusions on banks' recovery. Throughout the post-TARP announcement period, investors were able to gauge the long-run economic effects of capital infusions on individual institutions and the banking system as a whole. If stabilization of the system was successful, troubled institutions should have been beneficiaries of increased public confidence. In this respect, unlike most long-run event studies that focus on underreaction or overreaction to a specific information announcement (i.e., market inefficiency), we are interested in the total economic impact of capital infusions on the banking industry. Referring to the buy-and-hold reference portfolio results, CPP banks that repaid TARP funds by year-end 2010 had significant abnormal returns of about 4.7% in the interim between receiving and repaying funds. More importantly, in the quarter after repayment of TARP funds, CPP banks experienced economically large and significant buy-and-hold wealth gains of 14%, equivalent to approximately $329 billion. Linking our dynamic-recovery/event-study results, cross-sectional analyses show that long-run abnormal returns were significantly related to recovering financial condition over time.

Based on the empirical evidence, we conclude that TARP was instrumental in fostering the financial and stock price recoveries of CPP banks. A major policy implication is that troubled banks exposed to potential debt losses could benefit from capital infusions.

1.1. Related literature

TARP literature can be divided into studies of CPP banks' financial health and stock price performance. Related to our dynamic recovery analyses, previous studies examine the financial condition of CPP banks from a comparative static perspective. Compared to non-recipients, Bayazitova and Shivdasani (2012) find that CPP banks tended to be larger with greater funding uncertainties and weaker capital ratios, stronger asset quality, and higher commercial and industrial loans. Taliaferro (2009) reports evidence that CPP banks normally used TARP funds to improve their capital positions, rather than support lending.[9] Some characteristics of banks likely to participate in the CPP were: high leverage, high commitments and other opportunities for new lending, and exposure to troubled asset classes such as real estate loans. Duchin and Sosyura (2012) show that CPP funding was more probable among banks with political connections, lower capital adequacy, earnings, and liquidity, and larger size. Li (2012) also finds that political connections were a determinant of TARP funding and that most of this funding was used to bolster capital ratios as opposed to increase lending. Finally, Jordan et al. (2010) observe that the market-to-book ratios of CPP banks were lower than other banks. Lower market-to-book ratios were associated with higher expenses, nonaccrual assets, and real estate investments but lower non-interest and interest income. In general, these studies suggest that CPP banks were more financially distressed than non-recipients.

By contrast, evidence by Ng et al. (2010) indicates that CPP banks had higher profitability, as well as lower ratios of nonperforming loans to total loans, book-to-market, capital, and cash-to-deposits, than other banks. They infer that CPP participants generally had stronger financial condition than non-CPP banks prior to and during the initiation of TARP.

Some recent papers have documented the financial condition of recipient CPP banks after the receipt of TARP funds. Wilson and Wu (2012) show that early TARP exit by the end of 2009 was associated with higher CEO pay, bank size, capital, and financial condition compared to other CPP banks. Empirical analyses by Cornett et al. (2013) employ probit models to demonstrate that pre-crisis

[7] Originally, TARP funds were intended to purchase "toxic" assets from troubled institutions and address liquidity and credit flow problems in large institutions, but this approach was later abandoned by the Treasury in favor of capital infusions to avoid zombie banks with negative net worth and increased moral hazard risk.

[8] The government implemented a Small Business Lending Program from July to September 2011 to raise capital at smaller banks lending more heavily to small businesses. As of October 6, 2011, among 332 recipient banks, 137 banks used some of these funds to repay TARP obligations.

[9] For an in-depth analysis of the lending activities of CPP banks, see Contessi and Francis (2011).

health is not related to the probability of later repaying TARP funds. Especially among small banks, banks that later repaid TARP funds had improvements in loan portfolio quality, expense reduction, and income growth. Banks that missed dividend payments (deadbeats) tended to lose liquidity in an effort to make TARP payments, which further weakened their financial condition. Static Cox proportional hazard model results show that pre-crisis health was unrelated to the time to first repayment of TARP funds. Other hazard model results reveal that under-achievers (i.e., banks with below average pre-crisis profits) used TARP funds to increase capital and decrease loan loss provisions prior to repayment, whereas over-achievers (i.e., banks with above average pre-crisis profits) appeared to view TARP funds as a cheap source of financing to reinvest in other assets as their capital improved. Also, large banks repaid TARP funds faster than small banks, which they attribute to greater public scrutiny on big banks.

In sum, prior studies of CPP banks' financial condition focus on different points in time in the pre- and post-TARP period and obtain a variety of findings. Extending previous studies that utilize a comparative static approach to investigating bank health, the present paper seeks to better understand the dynamic changes in financial condition over time among CPP banks that repaid versus did not repay TARP funds.

Related to our long-run event study analyses, a smaller literature exists on the stock price reactions of CPP banks in response to TARP funding. Veronesi and Zingales (2010) hypothesize that government intervention to restore confidence in the presence of market failure should create value. Confirming this conjecture, short-run event study analyses in the announcement period October 10–14, 2008 (i.e., days −4 to 0) for 10 banks and securities firms forced to take CPP capital infusions in the first phase of the program indicated a total gain of $130 billion upon summing changes in these institutions' debt, equity, and derivative valuations. However, they find that, whereas preferred stockholders gained an estimated $6.7 billion, common stockholders lost about $2.8 billion in this 5-day event window. In view of the latter common stock wealth loss, Hoshi and Kashyap (2010) observe that some banks did not want to participate in the CPP due to signaling, debt overhang, and executive compensation issues.[10] Negative signaling could damage public opinion about potential future losses at participating banks, cause a loss of public confidence, and trigger a deposit run on a bank. Debt overhang occurs due to the fact that preferred stock is senior to common stock, such that bank recovery after capital infusions would not flow through to common shareholders until TARP funds were repaid. This problem could be exacerbated for banks with bonds selling at deep discounts, which would benefit from the new capital. Also, TARP provisions restricted executive compensation which raised risks of losing key managers and reducing management incentives to recover.[11] Together, consistent with the common stock results in Veronesi and Zingales, these drawbacks of participation could cause wealth losses.

Another study by Bayazitova and Shivdasani (2012) argues that government capital infusions signal private information about financial condition, thereby certifying that recipient banks are healthy and helping to resolve information asymmetries in addition to financial distress costs. Short-run event study analyses of stock price changes on days −1 and 0 with respect to October 14, 2008 point to significant wealth gains associated with the CPP announcement but not later dates when individual banks received capital infusions. The initial recipients gained 14.48% in this narrow event window, and 223 later recipients gained 4.01%.[12] Also, banks approved for TARP but declining participation did not experience any wealth effects. Further tests show that passage of legislation to tax employee bonuses at TARP institutions lowered their average excess returns by 8% but tended to increase returns among nonparticipating institutions. Also, positive (negative) wealth gains occurred on days −1 and 0 with respect to announcements of TARP repayment by institutions without (with) a stock issue announcement on the same day.[13] Although a large wealth gain appears to occur among initial recipients, as shown by Veronesi and Zingales, Morgan Stanley's stock price substantially increased in response to concomitant news about a deal to raise capital from Mitsubishi, a large commercial bank in Japan. Excluding this outlier, the initial recipients had almost zero wealth gains in their five-day event window. In general, initial TARP recipients experienced little or no common stock wealth gains in the opening days of capital infusions.

Closely related to our study, Ng et al. (2010) consider long-run price reactions among CPP banks. They divide the post-TARP period into two subperiods: (1) the CPP initiation subperiod in the last quarter of 2008 and first quarter of 2009, and (2) the post-CPP initiation subperiod in the second to fourth quarters of 2009. Banks receiving capital infusions in the last quarter of 2008 and first quarter of 2009 comprise the CPP bank sample ($n = 186$). Comparing buy-and-hold returns of CPP banks to those of non-CPP banks, CPP banks underperformed other banks by 6% in the former period but outperformed by 14.3% in the latter period. A multivariate regression analysis of buy-and-hold returns on banks with respect to CPP participation after controlling for CPP amount, market beta, size, and book-to-market risk factors confirmed these patterns in stock valuation over time. They inferred that undervaluation in the initiation period occurred due to negative market sentiment at that time.[14]

Some CPP portfolio return ambiguities are present in the Ng et al. study that lead to difficulty in interpreting their results. In the CPP initiation period, even though some participating banks did not receive funding until later in this period, they are counted in CPP portfolio returns for the entire period. Also, in the post-initiation period, some CPP banks had repaid government funds prior to the end of this period but are included in CPP portfolio returns for the entire period. These sampling procedures introduce ambiguities about the long-run effects of TARP funds on CPP banks' stock prices. Moreover, unlike their study, we follow the standard practice in long-run event studies of building reference non-CPP portfolios to control for size and book-equity/market-equity (BE/ME) in addition to applying a variety of test methods due to potential pitfalls in long-run event study analyses.

[10] Other reasons not to participate were required dividend payments to the government (i.e., 5% in the first 5 years and 9% thereafter) and limitation of dividend payments of 1% per quarter to common shareholders. A small percentage of TARP banks have missed their government dividend payments (see Wilson (forthcoming)).

[11] Cadman et al. (2012) report corroborating evidence that executive compensation affected acceptance of TARP funds and later likelihood of repayment of TARP funds and executive turnover. Also, Kim (2010) finds that TARP restrictions on executive pay lowered banks share prices, especially among larger and better performing banks.

[12] Kim (2010) also found positive wealth effects among TARP recipients on days −1 to +1 around this announcement date.

[13] Another study by Farruggio et al. (2013) finds similar short-run common stock wealth effects to the initial announcement of TARP. They also report negative (positive) wealth effects in a 5-day event window around announcements of capital infusions (repayments).

[14] Other studies focus on the wealth effects on borrowers of banks receiving TARP funds (Song and Uzmanoglu, 2011), wealth effects on banks' existing preferred stocks (Kim and Stock, 2012), and wealth effects of rescue efforts in different countries (King, 2009).

The next section overviews our dynamic recovery model and presents the empirical results. Section 3 describes the long-run event study and discusses the findings. Section 4 concludes.

2. Dynamic recovery model

2.1. A dynamic model of bank recovery

Bank prediction models have a long history as early warning systems (EWSs) of pending bank failures by regulatory agencies (e.g., see Meyer and Pifer (1970), Martin (1977), Sinkey (1979), Thomson (1991), Cole and Gunther (1995), and Wheelock and Wilson (2000), and many others). Studies confirm that regression models perform well as EWSs. Traditionally, regulators use static forecast models that compute predictors at a point in time prior to bank failure.

More recently, Shumway (2001) proposes a multi-period hazard model that estimates time-varying probabilities of financial distress prior to failure. He argues that one-period models ignore changing firm characteristics over time and, therefore, are unduly restricted to limited information about potential failure. Cole and Wu (2009) test Shumway's conjecture by comparing the forecasting accuracy of a time-varying hazard model versus a one-period probit model in terms of their ability to identify pending US bank failures in the periods 1985–1992 and 2009–2010. They find that, when predicting failures in the next year, the ability of the hazard model to exploit dynamic information improves its predictive power relative to the probit model. However, this advantage dissipates when attempting to predict failures two or three years into the future due to the information gap that exists in the data series. For these longer prediction horizons, neither type of model accurately predicts bank failures. They also find that inclusion of macroeconomic variables (e.g., real GDP growth rates and three-month Treasury bill rates) does not improve predictive accuracy.[15]

An obvious shortcoming of the static EWS approach is that potentially rich time-series dynamics of covariates are ignored. In this regard, Duffie et al. (2007) develop a dynamic hazard model of the likelihood of default that exploits time-series movements in explanatory covariates.[16] Applying the model to 2700 US firms in the period 1980–2004, they demonstrate that incorporating the dynamics of firm-specific and macroeconomic covariates enables maximum likelihood estimation of multi-period survival probabilities and boosts out-of-sample predictive performance relative to other available models.

Our dynamic model of bank recovery and resultant estimators are based on Duffie et al. (2007). Because we focus on recovery versus nonrecovery for CPP banks and ignore other types of exit, such as default, merger, acquisition, and liquidation, a simplified model setup with a singly-stochastic counting process is employed (rather than a doubly-stochastic formulation). Also, instead of focusing on the default process, we build a dynamic recovery model that estimates recovery probabilities. A Markov state vector $X(t)$ of bank-specific covariates determines variations in bank *recovery intensity* defined as $\lambda(t) = \Lambda(X(t), \beta) = \exp(\alpha + \beta\ X(t))$. The Markov state process $X(t)$ is assumed to follow an autoregressive time series process, or

$$X(t+1) = X(t) + \kappa(\theta - X(t)) + C\varepsilon(t+1), \tag{1}$$

where $\varepsilon(t)$'s are independent, standard-normal vectors at time t, and coefficients $\gamma = (\kappa, \theta, C)$ are estimated via maximum likelihood estimation (MLE) methods. Our sample contains n banks. During observation period $[0,T]$, CPP banks can only leave the sample due to recovery by time T. Let T_i denote the observed lifetime of the ith bank. If a bank's lifetime is cut short, let $\perp_i$ be the censoring indicator, where $\perp_i = 1$ if T_i is a recovery time, and $\perp_i = 0$ if T_i is a censoring time. The total number of recovery events is given by $\sum_{i=1}^{n} \perp_i$. Recovery likelihood is defined as

$$\mathcal{L}(\mathcal{F}; \gamma, \beta) = \mathcal{L}(X(t); \gamma) \times \mathcal{L}(X(t), \perp(t), T(t); \beta), \tag{2}$$

where

$$\mathcal{L}(X(t); \gamma) = \prod_{k=0}^{T} f_{X(k+1), X(k)}(X(k+1)|X(k); \gamma) \tag{3}$$

is the likelihood of vector $X(t)$ of covariates (assumed to follow the above mean-reversion dynamic process) with density function $f_{X(k+1),\ X(k)}$ being jointly normal distributed, and

$$\begin{aligned}\mathcal{L}(X(t), \perp(t), T(t); \beta) &= \prod_{i=1}^{n} G_{it}(\beta) \\ &= \prod_{i=1}^{n} \exp\left(-\int_{t_i^0}^{T_i} \Lambda(X(s), \beta) ds\right) \times [\exp(X_i(T_i)\beta)]^{\perp_i}\end{aligned} \tag{4}$$

is the likelihood of recovery for n banks, where t_i^0 is the time of first appearance for bank i in our sample. The above overall MLE problem can be decomposed into the separate problems

$$\sup_{\gamma} \mathcal{L}(X(t); \gamma) \tag{5}$$

and

$$\sup_{\beta} \mathcal{L}(X(t), \perp(t), T(t); \beta) = \sup_{\beta} \prod_{i=1}^{n} e^{-\int_{t_i^0}^{T_i} \Lambda(X(s),\beta) ds} [\exp(X_i(T_i)\beta)]^{\perp_i}. \tag{6}$$

When we obtain in-sample estimates of all coefficients ($\gamma = [\kappa, \theta, C]$) of dynamic processes and coefficients (β) of the recovery intensity function, it is straightforward to calculate the predicted probability of recovery. In this respect, the conditional expectation of the probability of nonrecovery can be computed from time T to $\tau > T$ in the future as

$$p(X(T), \tau) = E\left(e^{-\int_T^{\tau} \lambda(u) du} | X(T)\right), \tag{7}$$

and the probability of bank recovery to time $\tau > T$ is

$$q(X(T), \tau) = E\left(\int_T^{\tau} e^{-\int_T^{z} \lambda(u) du} \lambda(z) dz | X(T)\right). \tag{8}$$

The above forecasted nonrecovery and recovery probabilities are proven in Duffie et al. (2007). Unfortunately, in practice these calculations are onerous, as there are several variables in the recovery intensity function $\lambda(t)$, each with different autoregressive time series processes. When we replace the expectation with the average over Gibbs sample paths for all variables, brute-force Monte Carlo is extremely numerically intensive, and reliable results are difficult to obtain. Consequently, in Appendix A, we derive analytical approximations for these probabilities, which we later use to rank banks on recovery propensity in an out-of-sample test of model reliability. These new probability formulas for forecasted nonrecovery and recovery contribute to the literature, enabling bank regulators, academic researchers, and others to more readily utilize dynamic hazard (and recovery) models as early warning systems (EWSs).

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[15] For an application of a time-dependent Cox regression model to Australian firms, see Partington and Kim (2008).

[16] See also Duffie et al. (2009).

Table 1
Accounting and financial ratio measures of bank condition.

A. Capital adequacy	
1. *Eq_Assets*	Total equity capital/total assets
2. *Chrg_Cap*	Net charge-offs on loans and leases/total equity capital
3. *Tier1Lev*	Tier 1 leverage ratio
4. *Tier1Cap*	Tier 1 risk-based capital ratio
5. *CapRatio*	Total risk-based capital ratio
6. *EqGrowth*	One-year growth rate in total equity
7. *Zscore*	*Z*-score = Return on assets plus capital adequacy ratio/standard deviation of return on assets (3 years quarterly data)
B. Asset quality	
1. *Chrg_Assets*	Net charge-offs on loans and leases/total assets
2. *Chrg_Allow*	Net charge-offs on loans and leases/allowance for loan losses
3. *Prov_Assets*	Provision for loan and lease losses/total assets
4. *PD_RELoans*	Loans secured by real estate past due and nonaccruals/loans secured by real estate
5. *PD_Loans*	Total loans and leases past due and nonaccruals/total loans and leases
6. *PDRE_Assets*	Loans and leases past due plus nonaccruals plus other real estate owned/total assets
7. *SFMtg_Assets*	Single family (1–4) mortgages/total assets
8. *MFMtg_Assets*	Multifamily mortgages/total assets
C. Management	
1. *SDROA*	Standard deviation of return on assets (3 years quarterly data)
D. Earnings	
1. *ROA*	Net income after taxes/total assets
2. *Margin*	Net income/total income plus net gains on securities
3. *Div_Assets*	Dividends/total assets
E. Liquidity	
1. *Sec_Assets*	Total securities (at fair value)/total assets
2. *Trade_Assets*	Trading assets/total assets
3. *Cash1_Assets*	Cash plus federal funds sold plus Treasury bills plus municipal bonds/total assets
4. *Cash2_Assets*	Cash plus federal funds sold plus fair value of securities/total assets
5. *HTM_Assets*	Realized gains (losses) on held-to-maturity securities/total assets
6. *AFS_Assets*	Realized gains (losses) on available-for-sale securities/total assets
7. *Dep_Assets*	Total deposits/total assets
8. *NonDep_Assets*	Nondeposit funds/total assets
F. Sensitivity to market risk	
1. *DebtPD_Sec*	Debt securities past due and nonaccrual/total securities
2. *MortSec_Assets*	Mortgage-backed securities plus asset-backed securities/total assets
3. *Chg_Cash2*	Quarterly rate of change in the ratio of cash plus federal funds sold plus fair value of securities/total assets
4. *IntSensA_L*	Interest sensitive assets/interest sensitive liabilities
5. *CVIntInc*	Coefficient of variation of net interest income (standard deviation/mean based on 3 years of quarterly data)
6. *Complex*	Bank holding company complexity dummy variable, 0 for non-complex banks or 1 for complex banks
G. Synthetic CAMELS	
1. *CAMELS1*	Sum of decile rankings from 1 (low) to 10 (high) of capital, asset quality, management, earnings, liquidity, and sensitivity to market risk (see text for accounting and financial ratio proxies)
2. *CAMELS2*	Sum of distribution rankings from 1 (low) to 8 (high) of capital, asset quality, management, earnings, liquidity, and sensitivity to market risk (see text for accounting and financial ratio proxies)
H. Other	
1. *LogAssets*	Total assets (log)

2.2. Dynamic recovery model results

We collect accounting information from the FR Y-9C Consolidated Financial Statements for Bank Holding Companies in the sample period from first quarter 2002 to first quarter 2011. Data for smaller banks with total assets less than $500 million are excluded due to insufficient data to construct financial ratios. Requisite data was available for 272 CPP banks and 948 non-CPP banks with a total of 34,069 firm-quarters of data. In terms of demographics, California and Illinois well surpassed other states in terms of our CPP banks with each representing about 8% of sample banks. Regionally speaking, Southern states exceeded other areas of the country with about 36% of recipients in our sample. The leading Southern states in rank order were North Carolina, Virginia, Georgia, Florida, Tennessee, and Texas. Midwestern states accounted for about 31% of our CPP banks, with leading states (in rank order) Illinois, Missouri, Ohio, Indiana, Wisconsin, and Michigan. In the Northeast, the leading states were New York and Pennsylvania. The wide distribution of bank recipients across the United States reveals that the TARP program was national in scope and not limited to selected states.

We use the structure of the CAMELS rating system to guide the choice of 34 financial ratios and calculations for analysis. These variables are listed in Table 1. The CAMELS rating system is utilized by bank regulators to assess a bank's overall condition.[17] Definitions of each dimension of the CAMELS rating system as well as examples of variables under each dimension follow.

- Capital adequacy (C). Financial institutions are expected to maintain levels of capital that mitigate the adverse outcomes resulting from risks. Variables that provide information about the adequacy of banks' capital include total equity capital divided by total assets (*Eq_Assets*) and the one-year growth rate in total equity (*EqGrowth*).
- Asset quality (A). A financial institution that successfully manages and controls the risks that may affect the value or marketability of its assets is said to have high asset quality. Credit risks

[17] CAMELS is a numerical composite rating of overall bank financial condition assessed by regulatory supervisors ranging from 1 (best) to 5 (worst). See Feldman and Schmidt (1999) for a discussion of CAMELS scores, as well as Whalen (2005) for an application of hazard models to predicting CAMELS downgrades.

Table 2
Univariate results of accounting and financial ratio measures of bank condition in the dynamic recovery model.

Variable name	Intercept (std. error)	*t*-Stat.	Coefficient (std. error)	*t*-Stat.
A1* – *Eq_Assets*	−4.81 (0.20)	−24.05	10.13 (1.47)	6.89
A2 – *Chrg_Cap*	−3.79 (0.13)	−29.15	−1.12 (2.33)	0.48
A3* – *Tier1Lev*	−4.35 (0.24)	−18.13	0.55 (0.20)	2.75
A4* – *Tier1Cap*	−4.41 (0.16)	−27.56	0.48 (0.07)	6.86
A5* – *CapRatio*	−4.53 (0.17)	−26.65	0.50 (0.06)	8.33
A6* – *EqGrowth*	−3.88 (0.12)	−32.33	−0.36 (0.10)	3.60
A7 – *Zscore*	−3.90 (0.20)	−19.50	0.25 (0.70)	0.36
B1 – *Chrg_Assets*	−3.74 (0.17)	−22.00	−35.69 (54.99)	0.65
B2 – *Chrg_Allow*	−3.82 (0.20)	−19.10	0.06 (0.95)	0.06
B3 – *Prov_Assets*	−3.60 (0.17)	−21.18	−79.97 (48.23)	−1.66
B4 – *PD_RELoans*	−3.76 (0.22)	−17.09	−2.03 (3.74)	−0.54
B5 – *PD_Loans*	−3.56 (0.24)	−14.83	−6.45 (5.21)	−1.24
B6* – *PDRE_Assets*	−3.28 (0.25)	−13.12	−17.27 (7.74)	−2.23
B7 – *SMFtg_Assets*	−3.97 (0.27)	−14.70	0.78 (1.36)	0.56
B8* – *MFMtg_Assets*	−3.47 (0.18)	−19.28	−17.60 (7.6)	2.32
C1 – *SDROA*	−3.81 (0.12)	−31.75	0.24 (0.23)	1.04
D1* – *ROA*	−3.93 (0.13)	−30.23	140.84 (49.36)	2.85
D2 – *Margin*	−3.79 (0.16)	−23.69	−12.95 (40.25)	−0.32
D3* – *Div_Assets*	−3.85 (0.13)	−29.62	92.80 (30.80)	3.01
E1* – *Sec_Assets*	−4.60 (0.31)	−14.84	4.31 (1.47)	2.93
E2* – *Trade_Assets*	−3.88 (0.13)	−29.85	7.77 (3.23)	2.41
E3* – *Cash1_Assets*	−4.34 (0.20)	−21.70	5.35 (1.36)	3.93
E4* – *Cash2_Assets*	−4.93 (0.29)	−17.00	4.61 (0.96)	4.80
E5 – *HTM_Assets*	−3.82 (0.12)	−31.83	466.04 (1856.19)	0.25
E6 – *AFS_Assets*	−3.84 (0.13)	−29.54	236.49 (230.23)	1.03
E7* – *Dep_Assets*	−0.00 (0.73)	−0.00	−5.16 (1.01)	−5.11
E8* – *NonDep_Assets*	−4.40 (0.22)	−20.00	3.55 (1.03)	3.45
F1 – *DebtPD_Sec*	−3.83 (0.13)	−29.46	−4.82 (61.80)	−0.08
F2* – *MortSec_Assets*	−4.36 (0.24)	−18.17	5.02 (1.73)	2.90
F3 – *Chg_Cash2*	−3.81 (0.12)	−31.75	−1.60 (1.09)	−1.47
F4* – *IntSensA_L*	−4.72 (0.12)	−39.33	0.42 (0.01)	4.20
F5* – *CVIntInc*	−4.16 (0.18)	−23.11	0.03 (0.01)	3.00
F6* – *Complex*	−4.18 (0.16)	−26.13	1.21 (0.23)	5.26
G1 – *CAMELS1*	−4.66 (0.52)	−8.96	1.93 (1.15)	1.68
G2* – *CAMELS2*	−5.72 (1.02)	−5.61	4.73 (2.49)	1.90
H1* – *LogAssets*	−9.28 (0.90)	−10.31	0.36 (0.06)	6.00

The recovery rate is defined as $\Lambda(t) = \exp(\alpha + \beta\text{VAR})$, where VAR is a single predictor variable. Variable names coincide with accounting and financial ratio measures of bank condition shown in Table 1. The sample consists of 272 CPP banks, of which 72 repaid and 200 did not repay TARP funds by year-end 2010. Quarterly data are utilized from December 2007 to December 2010. Standard errors are shown in parentheses. Asterisks mark variables that are significant at the 5% level or higher, with the exception of G2 which is close to this level.

are of prime importance for this dimension. An example of a variable in this area is net charge-offs on loans and leases divided by total assets (*Chrg_Assets*).

- Management (M). This dimension relates to the ability of the board and management to operate the bank in a safe, sound, and efficient manner in all aspects. The three-year standard deviation of the return on assets (*SDROA*) is a proxy for this area.
- Earnings (E). The focus of this dimension is upon the quantity, quality, and trend of earnings. Ratios that provide information about earnings include net income after taxes divided by total assets (*ROA*) and dividends divided by total assets (*Div_Assets*).
- Liquidity (L). The financial institution's funds management practices should ensure that existing and future sources of liquidity match its funding needs, and these sources should not be excessively expensive or precarious in times of market-wide financial stress. Examples of liquidity variables include total securities divided by total assets (*Sec_Assets*) and total deposits divided by total assets (*Dep_Assets*).
- Sensitivity to market risk (S). This dimension relates to the degree to which changes in interest rates, foreign exchange rates, or commodity or equity prices can cause a decline in a financial institution's earnings or capital. Two of the variables used to measure market risk sensitivity are interest sensitive assets divided by interest sensitive liabilities (*IntSensA_L*) and the coefficient of variation of net interest income (*CVIntInc*).

We also aggregate selected variables into synthetic CAMELS scores. We compute the CAMELS1 variable by summing decile rankings of the following variables wherein ranks for each variable are ordered from 1 (low) to 10 (high) in terms of financial condition: equity capital plus reserves/total assets, gross charge-offs on loans/total assets, standard deviation of return on assets using three years of quarterly data, net income after taxes/total assets, cash plus federal funds sold plus Treasury bills plus municipal bonds/total assets, and quarterly rate of change in the ratio of cash plus federal funds sold plus fair value of securities/total assets. Benchmark cutpoints for forming decile ranks for each financial ratio are established using data from a stable banking period from 2002 to 2004, i.e., a decile rank of 1 (10) corresponds to low (high) financial health. The same decile cutpoints are used in later sample period years 2007 to 2010 to compute CAMELS1 scores. The CAMELS2 variable is similarly computed, except that banks are placed into groups (instead of decile ranks) based on their location in the distribution of each variable. We selected cutpoints for each variable to divide bank observations into eight groups that conform approximately to a normal distribution (e.g., cutpoints are set at ±0.5, ±1, and ±2 standard deviations from the mean for the capital adequacy and earnings measures). Banks are scored from 1 (low) to 8 (high) for each variable, and these scores are summed to obtain the CAMELS2 score.

Bank financial health is measured in terms of recovery rates estimated from our dynamic recovery model in the interim between receiving TARP funds in late 2008 or early 2009 and year-end 2010. Of 272 CPP banks with available Y-9C data, 72 fully repaid and 200 banks had not repaid TARP funds by year-end 2010. Banks repaying TARP funds in this time frame are classified as

Table 3
Correlation coefficients of significant accounting and financial ratio measures of bank condition.

	A1	A3	A4	A5	A6	B6	B8	D1	D3	E1	E2	E3	E4	E7	E8	F2	F4	F5	F6	G2
A3	0.77																			
A4	0.71	0.84																		
A5	0.69	0.80	0.98																	
A6	0.46	0.45	0.32	0.31																
B6	0.21	0.29	0.44	0.48	−0.03															
B8	0.08	0.14	0.17	0.18	−0.01	0.28														
D1	0.08	0.03	−0.01	−0.03	0.12	−0.33	0.10													
D3	0.11	0.03	−0.04	−0.05	0.05	−0.18	−0.09	0.09												
E1	0.07	0.10	0.26	0.26	−0.06	0.14	0.00	−0.01	−0.06											
E2	0.08	0.04	0.05	0.05	0.02	0.04	−0.09	−0.04	0.12	−0.03										
E3	0.05	0.14	0.30	0.30	−0.01	0.27	0.00	−0.07	−0.11	0.06	−0.06									
E4	0.07	0.15	0.39	0.40	−0.05	0.31	0.01	−0.07	−0.13	0.66	−0.04	0.62								
E7	−0.104	−0.03	0.14	0.15	−0.22	0.37	0.14	−0.11	−0.20	0.10	−0.06	0.33	0.32							
E8	−0.28	−0.29	−0.44	−0.45	0.02	−0.45	−0.17	0.08	0.13	−0.14	0.03	−0.36	−0.36	−0.86						
F2	0.02	0.07	0.20	0.20	−0.03	0.17	0.00	−0.06	−0.09	0.64	−0.06	−0.04	0.44	0.09	−0.10					
F4	0.10	0.11	0.12	0.11	0.03	0.00	0.04	0.07	−0.04	−0.06	0.05	0.10	0.06	−0.06	0.00	−0.07				
F5	0.08	−0.01	0.04	0.04	0.07	0.09	0.04	0.07	−0.04	0.00	0.07	0.01	−0.01	0.02	−0.03	0.06	0.08			
F6	−0.00	−0.03	−0.04	−0.07	−0.01	−0.10	−0.16	0.11	0.07	−0.18	−0.19	−0.05	−0.11	0.10	−0.10	−0.05	0.25	0.03		
G2	0.18	0.18	0.17	0.15	0.16	−0.14	−0.15	0.30	0.04	0.05	−0.07	0.39	0.30	0.01	−0.06	−0.07	0.07	0.04	0.12	
H1	0.19	0.21	0.30	0.32	0.22	0.34	0.06	−0.14	0.00	0.11	0.12	0.17	0.26	0.05	−0.14	0.15	0.01	0.14	−0.12	−0.03

Estimated correlation coefficients between significant univariate variables in the dynamic recovery model from December 2007 to December 2010 (see Table 2). Variable names coincide with accounting and financial ratio measures of bank condition shown in Table 1.

Table 4
Results of accounting and financial ratio measures of bank condition in dynamic recovery model.

Variable names	Full model	*t*-Stat.	Reduced model	*t*-Stat.	Reduced model excluding eight large banks	*t*-Stat.
Constant	−13.89 (3.08)	−4.51	−10.12 (1.24)	−8.16	−9.87 (−1.48)	−6.67
A1* – *Eq_Assets*	20.56 (7.72)	2.66	13.71 (6.24)	2.20	14.28 (6.38)	2.24
A6 – *EqGrowth*	−13.59 (11.18)	−1.22				
B6* – *PDRE_Assets*	−3.60 (0.85)	−4.24	−3.18 (0.69)	−4.61	−3.77 (0.72)	−5.24
B8 – *MFMtg_Assets*	−3.77 (9.42)	−0.40				
D1* – *ROA*	156.35 (45.74)	3.42	141.21 (37.66)	3.75	189.32 (60.41)	3.13
D3* – *Div_Assets*	275.99 (114.41)	2.41	207.78 (102.87)	2.02	194.94 (100.54)	1.94
E1 – *Sec_Assets*	4.05 (3.41)	1.29				
E2 – *Trade_Assets*	0.19 (6.79)	0.03				
E3 – *Cash1_Assets*	3.51 (2.91)	1.21				
E7 – *Dep_Assets*	3.96 (2.36)	1.68				
F2 – *MortSec_Assets*	0.59 (3.35)	0.18				
F4* – *IntSensA_L*	0.18 (0.07)	2.57	0.12 (0.06)	2.00	0.12 (0.06)	2.00
F5* – *CVIntInc*	0.03 (0.01)	3.00	0.03 (0.01)	3.00	0.02 (0.01)	2.00
F6 – *Complex*	0.19 (0.35)	0.54				
G2 – *CAMELS2*	−2.55 (1.85)	−1.38				
H1* – *LogAssets*	0.31 (0.12)	2.58	0.29 (0.07)	4.14	0.27 (0.09)	3.00

The recovery rate is defined as $\Lambda(t) = \exp(\alpha + \sum_i \beta_i \mathrm{VAR}_i)$, where VAR is multiple predictor variables. Variable names coincide with accounting and financial ratio measures of bank condition shown in Table 1. The sample consists of 272 CPP banks, of which 72 repaid and 200 did not repay TARP funds by year-end 2010. Quarterly data are utilized from December 2007 to December 2010. Standard errors are shown in parentheses. The full model includes all significant univariate variables (see Table 2). The reduced model only includes predictors significant at the 5% level, which are marked with asterisks. For robustness purposes, another version of the reduced model is run excluding eight large CPP banks forced by the US Treasury to accept TARP funds (viz., Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan Chase, State Street Corporation, Morgan Stanley, and Wells Fargo).

recovered banks. As a first step, a univariate analysis of financial variables is performed to identify covariates that significantly discriminate between repaying (recovered) and nonrepaying (nonrecovered) CPP banks.[18] Variables that significantly (at the 5% level or higher) affect recovery rates are marked with an asterisk in Table 2 (e.g., the positive and significant estimated β coefficient for variable A1 indicates that a higher total equity capital/total assets ratio is associated with increased recovery rates). A total of 21 out of 36 variables are significant univariate discriminators with respect to repaying versus nonrepaying CPP banks.

The univariate results in Table 2 indicate that banks repaying TARP funds improved across all CAMELS performance dimensions. The most significant variables with large *t*-statistics exceeding 4.0 are total equity capital/total assets (*Eq_assets*), Tier 1 risk-based capital ratio (*Tier1Cap*), total risk-based capital ratio (*CapRatio*), cash plus liquid assets/total assets (*Cash2_Assets*), total deposits/total assets (*Dep_Assets*), interest sensitive assets/interest sensitive liabilities (*IntSensA_L*), bank holding company complexity (*Complex*), and total assets (*LogAssets*). Thus, larger, more complex banks with higher capital levels, more cash, less deposit funding, and positive interest sensitivity tended to have faster recovery rates. Additional covariates that are significant (at the 5% level) suggest that recovery rates improved for banks with less credit risk (i.e, *PDRE_Assets* measuring loans and leases past due plus nonaccruals plus other real estate owned/total loans and leases), higher profits (i.e., *ROA* or return on assets), faster rising profits (i.e., *CVIntInc* defined as the coefficient of variation of net interest income over the past three years), higher securities exposures (i.e., *Sec_Assets* or total securities/total assets, *Trade_Assets* or trading assets/total

[18] Some CPP banks made partial repayments prior to full repayment. We define recovery as full repayment of TARP funds.

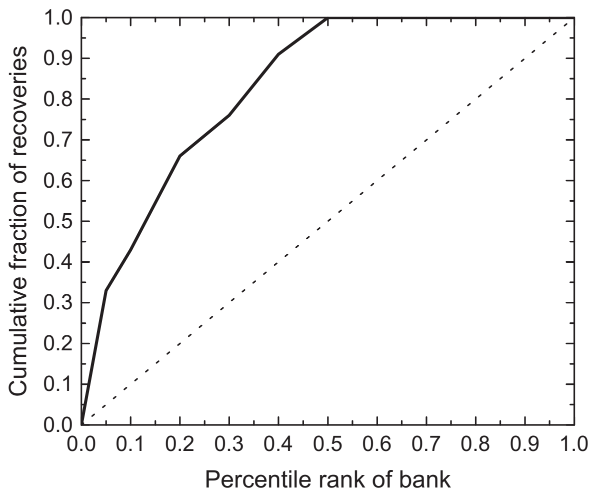

Fig. 1. Out-of-sample power curve for three-quarter recovery prediction from January 2011 to September 2011 for CPP banks not repaying TARP funds by year-end 2010. The power curve shows the relation between the fraction of late recoveries among CPP banks ($n = 132$) (i.e., banks not repaying TARP funds by year-end 2010 but recovering within three quarters in 2011) and their estimated recovery probabilities at year-end 2010 using the reduced model in Table 4 (e.g., 0.1 coincides with banks ranked in the top 10% at year-end 2010).

assets, and *MortSec_Assets* or mortgage-backed securities plus asset-backed securities/total assets), and stronger overall financial condition (i.e., *CAMELS2* measuring the sum of the CAMELS distribution rankings). We infer that these covariates played important roles in explaining recovery rates of banks repaying TARP funds.

Table 3 shows the correlation matrix for these 21 variables. In the second step, we dropped variables with correlation coefficients higher than 0.65 with another variable and lower univariate significance in Table 2 than its counterpart. This step eliminated five variables (viz., A3, A4, A5, E4, and E8) to yield 16 predictors (viz., A1, A6, B6, B8, D1, D3, E1, E2, E3, E7, F2, F4, F5, F6, G2, and H1).

In the third and last step, we estimate the dynamic recovery model using the 16 chosen predictors. Table 4 shows the results for the full model containing all predictors. Seven variables (B6, B8, E1, E2, E3, F2, and F6) are insignificant at the 5% level. Two other variables (E7 and G2) exhibit opposite signs from the univariate results suggesting collinearity with other predictor variables. After dropping these variables, we obtain the reduced model containing the following seven predictors:

- A1 – Total equity capital/total assets.
- A6 – Loans and leases past due plus nonaccruals plus other real estate/total assets.
- D1 – Net income after taxes/total assets.
- D3 – Dividends/total assets.
- F4 – Interest sensitive assets/interest sensitive liabilities.
- F5 – Coefficient of variation of net interest income (standard deviation).
- H1 – Total assets (log).

As shown in Table 4, these variables are significant (at the 5% level or higher) determinants of CPP bank recovery. For robustness purposes, we re-ran the reduced model excluding eight large CPP banks that were forced by the US Treasury to accept TARP funds (viz., Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan Chase, State Street Corporation, Morgan Stanley, and Wells Fargo) with little change in results. In general, the dynamic recovery model results suggest that recovering banks over time exhibited stronger overall financial condition than nonrecovering banks, as evidenced by higher capital, loan quality, profits, dividends, liquidity (i.e., more short-term, interest-sensitive assets than liabilities), and asset size. These results tend to be consistent with previously-cited studies by Cornett et al. (2013) and Wilson and Wu (2012) that find capital and asset size differences among repaying CPP banks. However, we also find that profitability and associated dividend payments as well as balance sheet liquidity[19] help to explain bank recovery.

As an out-of-sample test of the reliability of the reduced model, as discussed at the end of Section 2.1, we estimated the recovery probabilities of CPP banks that had not repaid TARP funds by year-end 2010 over a three-quarter horizon in 2011.[20] These CPP banks are ranked on their forecasted recovery probabilities and then compared to actual repayments of CPP banks from January to September in 2011. Fig. 1 summarizes the power curve results. The curve shows that, among the nonrepaying CPP banks in the top 20% of forecasted recovery probabilities, about 65% of these banks repaid TARP funds within the forecast horizon. Over 90% of banks repaying TARP funds in the next three quarters were ranked in the top 40% of forecasted recovery probabilities. Also, following Duffie et al. (2007, p. 665), we computed an accuracy ratio defined as twice the area between the power curve and the dashed 45° line in Fig. 1. A negative accuracy ratio indicates no out-of-sample predictive power. We estimate this ratio to be 69%. Based on the power curve and accuracy ratios, we infer that the reduced model does a good job of identifying CPP banks that are likely to repay TARP funds in the near future.

An anonymous referee noted that CPP banks repaying TARP funds may well have been motivated in part by executive compensation constraints imposed by US Treasury on February 4, 2009. At that time, total annual CEO compensation was restricted to $500,000. To test this conjecture, we collect executive compensation data from the Corporate Library. From each bank's 2008 proxy statements, we use the aggregate total dollar value of each form of CEO compensation in the summary compensation table. CEO compensation data was available for 124 of our 272 sample banks.[21] We subsequently augmented the reduced model with a new variable measuring CEO compensation restrictiveness, which is defined as zero if compensation is below $500,000 and total compensation minus $500,000 otherwise. For this variable, the estimated coefficient was positive (i.e. 0.05) and significant at the 1% level (i.e., *t*-statistic of 2.72). Hence, as the restrictiveness of the executive compensation constraint increased, the probability of TARP repayment or recovery increased. In this augmented reduced model, total assets is insignificant, which is not surprising due to increasing executive compensation with bank size. Because other variables remain significant in the reduced model, the results affirm that recovering banks had stronger financial condition than other banks.

In view of differences in the financial condition of repaying and nonrepaying CPP banks, we next evaluate whether investors were able to identify recovering CPP banks. If so, recovering CPP banks should have experienced higher stock prices than nonrecovering CPP banks. To investigate this conjecture, we conduct a long-run event study of CPP banks' stock prices, in addition to cross-sectional analyses of the relation between abnormal stock returns and recovery rates of CPP banks over time.

[19] Cornett et al. (2013) do find large banks repaying TARP funds sooner than other banks had higher unused loan commitments/total loan commitments ratios, which they interpret as indicating higher liquidity. However, if a bank had low total loan commitments, this ratio would not be informative about its liquidity.

[20] As cited in an earlier footnote, a number of small banks used funds from the Small Business Lending Program to repay TARP obligations from July to September 2011. However, these small banks were not in our sample CPP banks due to unavailability of requisite accounting and financial data.

[21] Only 10 of these 124 banks with CEO compensation data had executive compensation below $500,000, which means that most banks were constrained by the Treasury rule.

3. Long-run event study

According to Hoshi and Kashyap (2010), the eventual success or failure of the CPP program could not be determined at the time of its initial implementation. The authors cite future economic growth, exit from current government intervention programs, and regulatory reform as the primary factors that would shape the actual outcome. In this section we investigate the long-run impact of capital infusions on the common stock values of participating banks. Among the 272 CPP banks with available financial data, 195 banks had publicly-traded stock, of which 63 banks repaid and 132 banks had not repaid TARP funds by year-end 2010. The time period between receipt of TARP funds and later payment provides a well-defined event period around which to organize our analyses.[22] If banks' recovery was accelerated by capital infusions, we expect abnormal common stock wealth gains relative to similar nonparticipating banks in this long-run event window. We also investigate CPP banks' stock prices before and after this TARP funding event period.

Due to the potential for misspecified test statistics in long-run event studies, Lyon et al. (1999) evaluate alternative approaches for testing long-run abnormal returns that attempt to control for new listing, rebalancing, skewness, and cross-sectional dependence biases, in addition to bad model problems of asset pricing (see Barber and Lyon, 1997; Kothari and Warner, 1997; Fama, 1998). They find that well-specified test statistics in random samples are generated by two methods: (1) reference portfolio abnormal returns that control for firm characteristics using buy-and-hold returns and (2) calendar-time portfolio abnormal returns based on an asset pricing model. Due to advantages and disadvantages of these methods, we follow their recommendation to employ both methods in long-run event study tests.

3.1. Reference rortfolios

We construct nine reference portfolios from non-CPP bank holding companies with available financial data and publicly-traded stock. Portfolios are formed using 3×3 sorts with respect to bank size and book-equity/market-equity (BE/ME). Due to volatile common stock prices in the TARP funding period, size is proxied by the book value of equity rather than market value. Reference portfolios are formed as follows:

1. The book value of equity is gathered for each non-CPP bank on the last day of the quarter from 2008 to 2010.
2. Non-CPP banks are ranked on the book value of equity on the last day of quarter t to form three groups of small, medium, and large banks, respectively.
3. Each size group is further partitioned into three subgroups on the basis of their respective BE/ME ratios on the same day.
4. Daily returns of the size-BE/ME reference portfolios are computed from the first day of quarter $t+1$ to the last day of the same quarter.

Using this procedure, the total number of reference portfolio banks varies from 110 to 140 banks over time due to bank failures, mergers, and new charters.

We compute long-run portfolio returns in two ways. The cumulative rebalanced return of reference portfolio i from time T to τ is commonly defined as follows:

$$R_i^{reb}(T,\tau) = \prod_{t=T}^{\tau}\left[1 + \frac{\sum_{k=1}^{N_{it}} R_{kt}}{N_{it}}\right] - 1, \tag{9}$$

where R_{kt} is the return on security k on day t, and N_{it} denotes the number of securities on day t for portfolio i. Lyon et al. (1999) argue that this long-run return suffers from monthly rebalancing bias due to maintaining equal weights as well as new listing bias. Consequently, they propose the following buy-and-hold cumulative return for reference portfolio i from time T to τ:

$$R_i^{bh}(T,\tau) = \sum_{k=1}^{N_{iT}} \frac{\prod_{t=T}^{\tau}(1+R_{kt}) - 1}{N_{iT}}. \tag{10}$$

This return measures the passive equally-weighted investment performance of all securities in the reference portfolio (i.e., no monthly rebalancing or inclusion of newly-listed firms in the investment period). Table 5 compares average quarterly returns based on rebalanced versus buy-and-hold return equations from January 2008 to December 2010. Similar to Lyon et al. (1999), we find that rebalanced returns are upwardly biased relative to buy-and-hold returns in 8 out of 9 size-BE/ME reference portfolios.

Table 5
Comparison of average quarterly CPP bank returns on size-BE/ME sorted reference portfolios based on rebalanced versus buy-and-hold returns: sample period from January 2008 to December 2010.

	Rebalanced return (%)	Buy-and-hold return (%)	Difference (%)
S-L	1.24 (8.86)	−1.61 (8.87)	2.85
S-2	4.25 (8.50)	3.61 (8.69)	0.64
S-H	1.24 (15.76)	−7.19 (15.73)	8.43
M-L	0.79 (15.41)	−0.49 (13.98)	1.28
M-2	−2.21 (13.62)	−4.53 (14.41)	2.42
M-H	−7.17 (16.42)	−14.65 (14.92)	7.48
L-L	0.36 (10.70)	0.36 (11.28)	0
L-2	3.83 (18.20)	3.20 (17.87)	0.63
L-H	−4.71 (23.88)	−7.47 (25.18)	2.76

Nine reference portfolios for non-CPP banks are constructed by sorting into three size groups (small, medium, and large) and three BE/ME groups (low, 2, and high). The total non-CPP bank sample varies over time from 110 to 140 banks due to failure, mergers, and new charters. Long-run returns are computed using both rebalanced versus buy-and-hold formulas and shown in average quarterly terms. Standard deviations are shown in parentheses.

3.2. Event study tests and results

Reference portfolio tests are performed using the long-horizon abnormal return for asset i defined as

$$AR_{iL} = R_{iL} - E(R_{iL}), \tag{11}$$

where R_{iL} is the $L = \tau - T$ period return for asset i, $E(R_{iL})$ is the L period expected return on the size-BE/ME reference portfolio for the ith asset, and expected returns are estimated using both the rebalanced or buy-and-hold returns. We also repeat this test using matched-control non-CPP banks in the same size group with the closest BE/ME ratio to each CPP bank.

Calendar-time portfolio methods have the advantage of mitigating cross-sectional dependence of sample returns, which is likely an issue in the present case due to event-date clustering and industry clustering (see Loughran and Ritter, 1995; Brav et al., 1995; Brav and Gompers, 1997; Mitchell and Stafford, 2000). Following Jaffee (1974) and Mandelker (1974), we utilize two calendar-time portfolio approaches. One approach is to estimate an asset pricing model using a portfolio of firms that had an event under study within a chosen time span and test the null hypothesis that the mean monthly excess return as proxied by the intercept term (α_i) is zero. Here we estimate the Fama–French (see Fama and French, 1992, 1993, 1995) three-factor model augmented with momentum for CPP banks in the period October 1, 2008–December 31, 2010:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + m_i MOM_t + \epsilon_{it}, \tag{12}$$

[22] The CPP program opened on October 14, 2008 and closed on November 19, 2009.

Table 6
Long-run event study results based on reference portfolios for CPP banks repaying TARP funds by year-end 2010.

Event window	Abnormal return (%)	*t*-Statistics
Panel A. Rebalanced returns		
Receipt to repayment	3.52	1.51
One quarter before receipt	−3.84	−1.51
One quarter after receipt	−0.07	−0.17
One quarter after repayment	8.37	2.94
Panel B. Buy-and-hold returns		
Receipt to repayment	4.71	1.96
One quarter before receipt	−5.22	−2.13
One quarter after receipt	−2.29	−0.55
One quarter after repayment	14.02	4.74
Panel C. Control bank returns		
Receipt to repayment	4.98	1.66
One quarter before receipt	0.30	0.08
One quarter after receipt	0.06	0.01
One quarter after repayment	9.74	2.34

This table presents average quarterly long-run abnormal return estimates for CPP banks repaying TARP funds by year-end 2010 ($n = 63$) in four different event windows: (1) the period from receipt to repayment of TARP funds, (2) one quarter before receiving TARP funds, (3) one quarter after receiving TARP funds, and (4) one quarter after repayment of TARP funds. Estimated abnormal return results are presented for reference portfolio and matched-control approaches. Nine reference portfolios for non-CPP banks are constructed by sorting into three size groups and three BE/ME groups (n ranges from 110 to 140 over time). For the reference portfolio approach, CPP banks' long-run abnormal returns are estimated using rebalanced versus buy-and-hold return formulas. Matched-control abnormal returns are estimated by pairing each CPP bank with a non-CPP bank using the size group and closest BE/ME ratio to each CPP bank. Results for the receipt to repayment event window are in terms of average quarterly abnormal returns.

where R_{it} is the daily return on the value-weighted portfolio of banks, R_{ft} is the daily Treasury bill return, R_{mt} is the daily return on the value-weighted CRSP market index, SMB_t is the daily value-weighted return on small stocks minus big stocks, HML_t is the daily value-weighted return on high BE/ME stocks minus low BE/ME stocks, MOM_t is the daily return on high minus low return portfolios in the past year, and ϵ_{it} is the error term. All predictors are gathered from Kenneth French's website. Results are generated for all CPP banks ($n = 195$), CPP banks repaying TARP funds by year-end 2010 ($n = 63$), and non-CPP banks ($n = 195$). We should note that a major disadvantage of this approach is a poorly defined event window, as we cannot investigate abnormal returns in different event windows defined around the receipt and later repayment of TARP funds as used in the reference portfolio approach. A second approach is to compute Eq. (11) each month for an individual CPP bank relative to its non-CPP reference portfolio, average these cross-sectional abnormal returns for all CPP banks in each month, and then obtain the grand mean of these monthly portfolio averages over the sample period.

Table 6 reports the reference portfolio results. Focusing on the receipt to repayment window, after rescaling abnormal returns in terms of average quarterly abnormal returns due to differences in event window lengths across repaying banks, panels A, B, and C show that recovering CPP banks had rebalanced abnormal returns of 3.52%, buy-and-hold abnormal returns of 4.71%, and matched-control abnormal returns of 4.98%, respectively. The latter two results are significant at the 10% level or higher. In the quarter before receipt of TARP funds, these three methods generate abnormal returns equal to −3.84%, −5.22%, and 0.30%, respectively, with significant negative buy-and-hold results. In the quarter after receipt of TARP funds, abnormal returns were insignificantly different from zero, i.e., −0.07%, −2.29%, and 0.06% for rebalanced, buy-and-hold, and control bank returns, respectively. Lastly, in the quarter after repayment of TARP funds, economically large and statistically significant wealth gains of 8.37%, 14.02%, and 9.74% occurred, respectively. Using the buy-and-hold returns, we estimate

Table 7
Long-run event study results based on reference portfolios for CPP banks taking into account large banks forced to accept TARP funds repaying TARP funds by year-end 2010.

Event window	Abnormal return (%)	*t*-Statistics
Panel A. CPP banks excluding eight large banks		
Receipt to repayment	1.54	0.64
One quarter before receipt	−2.25	−0.61
One quarter after receipt	−2.47	−0.52
One quarter after repayment	7.75	2.16
Panel B. Eight large CPP banks		
Receipt to repayment	2.53	0.60
One quarter before receipt	14.00	2.60
One quarter after receipt	−1.17	−0.09
One quarter after repayment	27.88	2.36

This table repeats buy-and-hold abnormal return results in Table 6 for two subsamples. Panel A provides results for CPP banks repaying TARP funds by year-end 2010 excluding eight large banks ($n = 55$) forced by the US Treasury to accept TARP funds (viz., Ban of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan Chase, State Street Corporation, Morgan Stanley, and Wells Fargo). Panel B gives results for these eight banks. Estimated buy-and-hold abnormal return results are presented for reference portfolios based on sorting non-CPP banks into three size groups and three BE/ME groups (n ranges from 110 to 140 over time). Results for the receipt to repayment event window are in terms of average quarterly abnormal returns.

the total wealth gain for CPP banks in this post-repayment quarter to be approximately \$329 billion. These large wealth gains in the post-repayment window indicate that investors perceived repayment of TARP funds as good news about the expected future performance of CPP banks. While the receipt of the capital infusion could be viewed as a positive, there remained great uncertainty as to the success of the inflows. The uncertainty was removed with the repayment. Indeed, the fact that the regulatory authorities allowed the repayment represented a certification of the financial stability of the repaying banks, a fact that shows up in our event study results.

As pointed out by an anonymous referee, it is possible that part of the post-repayment wealth gain was attributable to banks getting out of onerous compensation restrictions. Consequently, we re-ran the event study tests in Table 6 using 33-out-of-63 sample banks for which CEO executive compensation was available (see Section 2.2). Only 2 of these 33 banks had CEO compensation below the \$500,000 Treasury restriction. We ran a cross-sectional regression using buy-and-hold abnormal returns in the quarter after repayment of TARP funds as the dependent variable and CEO compensation divided by \$500,000 as the independent variable. The estimated coefficient of 0.24 is significant at the 10% level (t-statistic of 1.89), which suggests that bank shareholders indeed benefited from removing compensation restrictions via repayment.

Another observation from the results in Table 6 is that shareholders were only partially able to discern recovering banks from other CPP banks prior to repayment of TARP funds. Thus, our results suggest some degree of opaqueness in banking.[23]

Among CPP banks, a subset of nine large banks were forced by the US Treasury to accept \$125 of the total \$205 billion in TARP funds paid out.[24] Dropping Wachovia due its merger with Wells Fargo, Table 7 repeats the buy-and-hold reference portfolio results in Table 6 excluding these eight banks. Again, the largest wealth gains occurred in the quarter after repayment of TARP funds, with a signif-

[23] Comparing the credit ratings of banks and nonfinancial firms, Morgan (2002) concludes that banks are more opaque than other firms. By contrast, comparative analyses of the stock price efficiency of banks and nonfinancial firms by Flannery et al. (2004) finds little or no evidence to support bank opaqueness.

[24] Bank of America (\$15 billion), Bank of New York Mellon (\$3 billion), Citigroup (\$25 billion), Goldman Sachs (\$10 billion), JP Morgan Chase (\$25 billion), State Street Corporation (\$2 billion), Merrill Lynch (\$10 billion), Morgan Stanley (\$10 billion), Wachovia (\$5 billion), and Wells Fargo (\$20 billion).

icant average abnormal return of 7.75% for this sample of banks. Other event windows generated wealth gains with similar signs as in Table 6 but are insignificant. For the eight large banks, abnormal returns in this post-repayment quarter averaged 27.88% resulting in wealth gains of approximately $209 billion, well exceeding the original TARP payout of $115 billion to these banks. Clearly, capital infusions benefited beneficiary bank shareholders. Other banks had wealth gains of approximately $120 billion, again well exceeding TARP capital infusions.

Bayazitova and Shivdasani (2012) found that stress tests (viz., the Supervisory Capital Assessment Program or SCAP) announced by federal banking supervisors on May 7th, 2009 aided the stabilization of financial markets. These tests sought to determine if the largest 19 US bank holding companies had sufficient capital to withstand an unexpected economic downturn. SCAP buffers were zero for 9 of these 19 institutions, which means they had sufficient capital to cover estimated losses in an adverse scenario and pass Tier 1 capital ratios without any additional capital. Other banks with a positive capital buffer were required to develop a detailed capital plan to correct the shortfall. SCAP results published in the financial press generated considerable interest across the nation. As suggested by an anonymous referee, we examined stock price movements around the May 7th event date. Of the eight large banks in panel B of Table 7, 4 banks passed the stress tests (i.e., Bank of New York Mellon, Goldman Sachs, JP Morgan Chase, and State Street Corporation) and 4 failed (i.e., Bank of America, Citigroup, Morgan Stanley, and Wells Fargo). Interestingly, during the period from receipt of TARP funds on October 28th, 2008 to one day before the stress test announcement, banks that passed the stress tests had significant (at the 1% level) average abnormal returns of 22.97% compared to an insignificant average loss of −1.44% among failing banks. This difference in stock performance suggests that investors could distinguish between the financial conditions of passing and failing banks prior to the release of stress test results. Nevertheless, in a front page article of the *Wall Street Journal* of May 7th, 2009, FDIC Chairman Sheila Bair noted, "I think this will be a confidence-instilling announcement." (p. A2) Further analyses of two event windows for the post-announcement week May 7th to May 13th and post-announcement month May 7th to June 5th showed that average abnormal returns for both banks that passed and failed stress tests were positive but insignificant. We infer that, given that banks failing the tests did not experience negative wealth effects, the stress tests helped assure investors that troubled banks could survive even if economic conditions worsened.

Table 8 gives the calendar-time portfolio results for the sample period October 1, 2008 to December 31, 2010.[25] For CPP banks that repaid TARP funds by year-end 2010 ($n = 63$), the estimated α using daily returns in the sample period is positive but insignificant. By contrast, the estimated αs for all CPP banks ($n = 195$) as well as non-CPP banks ($n = 140$) are negative, with the latter exhibiting significance at the 10% level. We infer from this evidence that CPP banks did not experience the wealth losses of non-CPP banks in this sample period. In panel B, mean monthly calendar-time abnormal returns for CPP banks repaying TARP funds and all CPP banks are positive at 0.06% and 0.01% per day, respectively, albeit insignificantly different from zero; nonetheless, these positive abnormal returns are consistent with wealth gains documented above using the reference portfolio approach for CPP banks repaying TARP funds.

Lastly, we test for abnormal returns among CPP banks that had not repaid TARP funds by year-end 2010. As shown in Table 9, similar to the CPP banks that repaid their obligations, negative and significant abnormal returns occurred in the quarter before receiving capital infusions. Similar to repaying CPP banks, these banks had negative abnormal returns in the quarter after receiving capital infusions; however, a significant abnormal return of −6.27% for nonrepaying CPP banks occurred which is much larger than the insignificant −2.29% for repaying CPP banks. One year after receiving TARP funds, nonrepaying CPP banks continued to have negative average quarterly abnormal returns of −3.69% that are highly significant. We infer from these findings that investors were able to some extent to identify nonrecovering CPP banks.

Comparing our results to those of Ng et al. (2010), who estimate buy-and-hold abnormal returns of CPP banks relative to an unmatched portfolio of non-CPP banks, we also find increasing wealth gains over time after capital infusions. However, by parsing CPP banks into those that repaid versus those that had not repaid, we are able to clearly show that the repayment of TARP funds by CPP banks was the main factor contributing to large post-TARP funding wealth gains. CPP banks that had not repaid funds by year-end 2010 did not experience wealth gains.

Table 8
Long-run event study results based on calendar-time portfolio methods for CPP banks repaying TARP funds by year-end 2010.

	$\hat{\alpha}$ (%)	*t*-Statistics
Panel A. Factor model approach		
Repaid CPP banks	0.01	0.22
CPP banks	−0.04	−1.05
Non-CPP banks	−0.07	−1.71
	MMAR (%)	*t*-Statistics
Panel B. Mean monthly calendar-time abnormal returns		
Repaid CPP banks	0.06	1.51
CPP banks	0.01	1.06

Using the factor model approach, panel A shows estimates of intercept terms (α) for the Fama–French three-factor model augmented with momentum. Equal-weighted daily returns for CPP banks repaying TARP funds by the year-end 2010 ($n = 63$), all CPP banks ($n = 195$), and non-CPP banks ($n = 140$) are used in the period October 1, 2008 to December 31, 2010. Panel B gives results for the mean monthly calendar-time abnormal return approach. On a given calendar day, we calculate the abnormal return (AR_{it}) for each CPP bank using the returns on the nine size-BE/ME non-CPP banks' reference portfolios (R_{pt}), or $AR_{it} = R_{it} - R_{pt}$, and then compute the mean abnormal return (MAR_t) across all the CPP banks, or $\mathrm{MAR}_t = \sum_{i=1}^{N} AR_{it}/N$. A grand mean daily abnormal return is calculated as $\mathrm{MMAR} = \frac{1}{T}\sum_{t=1}^{T} \mathrm{MAR}_t$ for the period October 1, 2008 to December 31, 2010.

Table 9
Long-run event study results based on reference portfolios and buy-and-hold returns for CPP banks not repaying TARP funds by year-end 2010.

Event window	Abnormal return (%)	*t*-Statistics
One quarter before receipt	−4.03	−2.30
One quarter after receipt	−6.27	−2.88
One year after receipt	−3.69	−3.38

This table presents long-run abnormal return estimates for CPP banks that had not repaid TARP funds by year-end 2010 ($n = 132$) in three different event windows: (1) one quarter before receiving TARP funds, (2) one quarter after receipt of TARP funds, and (3) one year after receipt of TARP funds. Estimated abnormal return results are presented for the reference portfolio approach using buy-and-hold returns. Nine reference portfolios for non-CPP banks are constructed by sorting into three size groups and three BE/ME groups (n ranges from 110 to 140 over time). Results for the one year after receipt event window are in terms of average quarterly abnormal returns.

4. Cross-sectional analyses

Linking our dynamic-recovery/event-study results, we ran a cross-sectional regression of buy-and-hold abnormal returns for CPP banks on their estimated average quarterly recovery intensities. Recovery intensities are measured by the term λ (see Section 2.1) using the reduced model variables in Table 4 and,

[25] As a caveat, Lyon et al. (1999) point out that this test is prone to bad model problems when samples are gathered from a single industry. See also Fama (1998) for discussion of bad model problems in long-run event studies.

Table 10
Cross-sectional regression event study results using buy-and-hold returns and average recovery intensity for CPP banks.

	Constant ($\hat{\alpha}$)	Coefficient ($\hat{\beta}$)	Adj. R^2
Panel A. Full sample			
All CPP banks	−0.05 (−2.73)	1.20 (3.37)	0.06
CPP banks repaying	0.02 (0.63)	0.51 (1.75)	0.09
CPP banks not repaying	−0.12 (−5.23)	7.97 (5.11)	0.16
Panel B. Excluding eight large banks			
All CPP banks	−0.07 (−3.36)	2.45 (3.57)	0.07
CPP banks repaying	0.02 (0.54)	0.54 (0.90)	0.03
CPP banks not repaying	−0.13 (−4.99)	7.69 (4.77)	0.15

This table presents cross-sectional regression results for the following OLS regression model: $\overline{AR}_i = \alpha + \beta\bar{\lambda}_i$, where $\overline{AR}_i$ is the average quarterly abnormal return for the ith bank, and $\bar{\lambda}_i$ is the average quarterly recovery intensity defined in Section 2.1 using the reduced model variables in Table 4 (with t statistics in parentheses). We consider three different samples of CPP banks: (1) all CPP banks (n = 195), (2) CPP banks repaying TARP funds by year-end 2010 (n = 63), and (3) CPP banks not repaying TARP funds by year-end 2010 (n = 132). In the case of CPP banks repaying (not repaying) TARP funds, we use the interim from receipt of funds to their repayment (one year after receiving funds) to estimate long-run abnormal returns and average recovery intensities. Panel A includes all CPP banks. Panel B excludes eight large banks forced to accept TARP funds by the US Treasury (viz., Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan Chase, State Street Corporation, Morgan Stanley, and Wells Fargo).

therefore, capture multiple dimensions of financial recovery. Three different samples of CPP banks are used: (1) all CPP banks, (2) CPP banks repaying TARP funds by year-end 2010, and (3) CPP banks not repaying TARP funds by year-end 2010. For CPP banks repaying (not repaying) TARP funds, we use the interim from receipt of funds to their repayment (one year after receiving funds) to compute average quarterly long-run abnormal returns and average quarterly recovery intensities.

The results in panel A of Table 10 for the full sample reveal a highly significant (at the 1% level) estimated coefficient of 1.20 (with t-statistic of 3.37) between long-run wealth gains of CPP banks and their recovery intensities over time. Dropping the eight largest banks from the sample in panel B has little of no effect on the results. Thus, stock gains among CPP banks after receiving TARP funds were closely related to banks' probabilities of recovery as captured by multiple financial dimensions in our dynamic recovery model. Breaking out the full sample into CPP banks repaying and not repaying TARP funds, it is worth noting that this relation is strongest in the case of CPP banks not repaying TARP funds by year-end 2010. For nonrepaying banks the estimated coefficient is 7.97 (t-statistic of 5.11) compared to 0.51 (t-statistic of 1.75) for repaying banks. We interpret these results to be related to the large stock price increases among repayment banks in the quarter after returning TARP funds. More specifically, investors are forming expectations about nonrepaying banks' potential recovery based on their financial condition. By implication, our dynamic recovery model could be used by investors to help select stocks of banks most likely to repay TARP funds in the near future.

5. Conclusion

In an effort to assess whether capital infusions helped stabilize US banks and enhance their recovery, this paper investigated the long-run recovery experience of US commercial banks that received capital infusions from TARP funds distributed to distressed banks under the Capital Purchase Program (CPP). To do this, we performed financial condition and stock price analyses of CPP banks later repaying TARP funds by year-end 2010 relative to other CPP banks that had not repaid TARP funds.

Financial condition in the sample period from December 2007 to December 2010 was measured by means of a dynamic recovery model that estimates the probabilities of CPP banks repaying TARP funds relative to other CPP banks. Our results showed that recovering CPP banks tended to have higher capital, loan quality, profits, dividends, liquidity, size, and therefore overall financial condition than other CPP banks. Further out-of-sample tests in 2011 based on forecasted probabilities of bank recovery derived in the present paper supported the reliability of our dynamic recovery model. These new forecasted probabilities of expected future recovery contribute to the dynamic modeling literature by enabling bank regulators, academic researchers, and others to more readily utilize dynamic hazard (and recovery) models as early warning systems (EWSs). Further analyses confirmed earlier work by Bayazitova and Shivdasani (2012), who found that executive compensation restrictions prompted banks to repay TARP funds. As CEO compensation restrictions increased, the probability of repayment was higher, holding financial condition constant.

Common stock performance was investigated by means of a long-run event study of CPP banks using a variety of test methods. For recovering CPP banks, reference portfolio results revealed significant buy-and-hold abnormal returns of about 4.7% in the interim between receiving and repaying TARP funds, as well as economically larger and significant buy-and-hold wealth gains of 14.02% equivalent to approximately $329 billion in the quarter after repayment of TARP funds. This evidence lends some support for the notion that banks are opaque, as investors could only partially identify recovering banks before TARP repayments. Additionally, cross-sectional analyses showed that abnormal returns were significantly related to both removing onerous compensation restrictions and recovering financial condition. Consistent with Bayazitova and Shivdasani (2012), who found that banks experienced negative abnormal returns after passage of rules to restrict CEO compensation of TARP recipients, our cross-sectional tests indicated that abnormal returns after repayment of TARP funds were significantly related to executive compensation. Reflecting investor assessments of expected financial recovery, there was also a significant relationship between estimated long-run abnormal returns and average recovery intensities of CPP banks, especially among those that had not yet repaid TARP funds by year-end 2010. The latter finding suggests that, due to sizeable wealth gains after repayment of TARP funds, investors are attempting to use financial information to identify recovering banks. Hence, an unexpected result of the capital infusions is that market discipline among troubled banks appears to have been improved.

Empirical analysis of both financial statement data on the CPP banks and equity market responses to important events in the program suggest that TARP played an important role in fostering the recovery of these banks. Despite negative public perceptions at the time of its implementation as being harmful to "main street" America, our evidence suggests that the TARP program was successful for the banks in our sample. These results have potentially important policy implications for other financial systems and other time periods, especially for though not limited to troubled European banks that have been exposed to sovereign debt losses and that could benefit from similar capital infusions.

Appendix A. Derivation of approximations for recovery and nonrecovery probabilities

In this appendix, we derive an approximation for evaluating the following nonrecovery probability:

$$p(X(T),\tau) = E\left(e^{-\int_T^{\tau}\lambda(u)du}|X(T)\right) \approx E\left(e^{-\sum_{u=T+1}^{\tau}\lambda(u)}|X(T)\right)$$
$$= \int e^{-\sum_{u=T+1}^{\tau}\lambda(u)} \prod_{u=T+1}^{\tau} f(X(u)|X(T))dX(u). \tag{13}$$

To simplify the derivation, we begin by considering the one-period case, i.e., letting $\tau = T + 1$, but later generalize to the multi-period case. In this case, upon applying a Taylor expansion to the recovery rate function $e^{-\lambda(\tau)}$, we obtain

$$p(X(T),\tau) \approx \int e^{-\lambda(\tau)} f(X(\tau)|X(T))dX(\tau) = \int \left[\sum_{N=0}^{\infty}\frac{1}{N!}(-\lambda(\tau))^N\right] f(X(\tau)|X(T))dX(\tau). \tag{14}$$

A simple univariate model (to be extended to multiple variables shortly) can be specified as:

$$\lambda(\tau) = \exp[\alpha + \beta X(\tau)]. \tag{15}$$

Consequently, we can write

$$p(X(T),\tau) \approx \int \sum_{N=0}^{\infty}\frac{(-1)^N}{N!}\exp[N\alpha + N\beta X(\tau)] f(X(\tau)|X(T))dX(\tau) = 1 + \int \sum_{N=1}^{\infty}\frac{(-1)^N}{N!}\exp[N\alpha + N\beta X(\tau)] f(X(\tau)|X(T))dX(\tau), \tag{16}$$

with $X(t)$ following a mean reversion model, or

$$X(\tau) - X(T) = \kappa(\theta - X(T)) + C\varepsilon(\tau), \tag{17}$$

such that

$$f(X(\tau)|X(T)) = \frac{1}{\sqrt{2\pi}C}\exp\left\{-\frac{[X(\tau) - \kappa\theta - (1-\kappa)X(T)]^2}{2C^2}\right\}. \tag{18}$$

Integrating this function, for any given order N we get:

$$\begin{aligned}&\frac{(-1)^N}{\sqrt{2\pi}CN!}\int \exp[N\alpha + N\beta X(\tau)]\exp\left\{-\frac{[X(\tau)-\kappa\theta-(1-\kappa)X(T)]^2}{2C^2}\right\}dX(\tau)\\ &= \frac{(-1)^N}{\sqrt{2\pi}CN!}\int \exp\left\{-\frac{[X(\tau)-\kappa\theta-C^2N\beta-(1-\kappa)X(T)]^2}{2C^2}\right\}\\ &\quad\times\exp\left[N\alpha+\frac{C^2N^2\beta^2}{2}+N\beta(\kappa\theta+(1-\kappa)X(T))\right]dX(\tau)\\ &= \frac{(-1)^N}{N!}\exp\left[N\alpha+\frac{C^2N^2\beta^2}{2}+N\beta(\kappa\theta+(1-\kappa)X(T))\right].\end{aligned} \tag{19}$$

Finally, we obtain:

$$\begin{aligned}p(X(T),\tau) &\approx 1 + \sum_{N=1}^{\infty}\frac{(-1)^N}{N!}\exp\left[N\alpha + \frac{C^2N^2\beta^2}{2} + N\beta(\kappa\theta + (1-\kappa)X(T))\right]\\ &= 1 + \sum_{N=1}^{\infty}\frac{(-1)^N}{N!}\exp\left[\frac{C^2N^2\beta^2}{2} + N\beta(\kappa\theta + (1-\kappa)X(T)) + N\alpha\right],\end{aligned} \tag{20}$$

which converges when N is large. Extending the model to multiple periods, i.e., $n > 1$, we have:

$$\begin{aligned}&X(T+1) - (1-\kappa)X(T) = \kappa\theta + C\varepsilon(T+1)\\ &\frac{1}{1-\kappa}X(T+2) - X(T+1) = \frac{\kappa\theta}{1-\kappa} + \frac{C}{1-\kappa}\varepsilon(T+2)\\ &\vdots\\ &\frac{1}{(1-\kappa)^{n-1}}X(T+n) - \frac{1}{(1-\kappa)^{n-2}}X(T+n-1) = \frac{\kappa\theta}{(1-\kappa)^{n-1}} + \frac{C}{(1-\kappa)^{n-1}}\varepsilon(T+n).\end{aligned} \tag{21}$$

By summing these equations, we get

$$\frac{1}{(1-\kappa)^{n-1}}X(T+n) - (1-\kappa)X(T) = \kappa\theta\sum_{t=1}^{n}\frac{1}{(1-\kappa)^{t-1}} + C\sum_{t=1}^{n}\frac{\varepsilon(T+t)}{(1-\kappa)^{t-1}}. \tag{22}$$

Since $\varepsilon(T+n)$s are independent standard normal distributed, we can simplify the last term on the right-hand-side of Eq. (11) as

$$C\sum_{t=1}^{n}\frac{\varepsilon(T+t)}{(1-\kappa)^{t-1}} = \sqrt{\frac{1/(1-\kappa)^{2n}-1}{1/(1-\kappa)^2-1}}C\varepsilon(T+n), \tag{23}$$

so that

$$X(T+n) - X(T) = [1-(1-\kappa)^n](\theta - X(T)) + \sqrt{\frac{1/(1-\kappa)^2-(1-\kappa)^{2n-2}}{1/(1-\kappa)^2-1}}C\varepsilon(T+n). \tag{24}$$

In this multi-period case, the nonrecovery probability can be derived by replacing κ, θ, and C in Eq. (20) by

$$\begin{aligned}&\kappa \to [1-(1-\kappa)^n]\\ &\theta \to \theta\\ &C \to \sqrt{\frac{1/(1-\kappa)^2-(1-\kappa)^{2n-2}}{1/(1-\kappa)^2-1}}C.\end{aligned} \tag{25}$$

Finally, Eq. (20) can be easily generalized to multiple variables. By assuming there exist J interpretive variables, we have

$$p(X(T),\tau) \approx 1 + \sum_{N=1}^{\infty}\frac{(-1)^N}{N!}\times\exp\left[\frac{N^2\sum_{i=1}^{J}C_i^2\beta_i^2}{2} + N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha\right]. \tag{26}$$

Hence, for the recovery probability defined as

$$q(X(T),\tau) = E\left(\int_T^{\tau} e^{-\int_T^z\lambda(u)du}\lambda(z)dz|X(T)\right), \tag{27}$$

in the case of a singly-stochastic exit-counting process, we obtain

$$q(X(T),\tau) = 1 - p(X(T),\tau) \approx \sum_{N=1}^{\infty}\frac{(-1)^{N+1}}{N!}\exp\left[\frac{N^2\sum_{i=1}^{J}C_i^2\beta_i^2}{2} + N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha\right]. \tag{28}$$

We observe that, as N becomes large, the two expansion series in Eqs. (20) and (28) become very volatile. Since there is numerically no way to choose the correct order number N of the expansions, this approach is untenable.[26]

In practice, we know the average value of recovery intensity $\lambda(t) = \exp(\alpha + \beta X(t))$ is quite small[27] and that all the variables are normally distributed around their mean values. As such, there exists a cutoff N_c for the order number N. Thus, our final approximations for the nonrecovery and recovery probabilities, respectively, are as follows:

$$\begin{aligned}p(X(T),\tau) &\approx 1 + \sum_{N=1}^{N_c}\frac{(-1)^N}{N!}\exp\left[\frac{N^2\sum_{i=1}^{J}C_i^2\beta_i^2}{2} + N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha\right],\\ q(X(T),\tau) &\approx \sum_{N=1}^{N_c}\frac{(-1)^{N+1}}{N!}\exp\left[\frac{N^2\sum_{i=1}^{J}C_i^2\beta_i^2}{2} + N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha\right].\end{aligned} \tag{29}$$

with the cutoff N_c being the first order number N which satisfies

$$A(N+1) > A(N), \tag{30}$$

[26] This problem arises from the normality assumption for interpretative variables in the recovery function. Under normality, recovery intensity function $\lambda(t) = \exp(\alpha + \beta X(t))$ has some small probability to become very large, which leads to a trivial recovery rate $\exp(-\lambda(t))$. When applying a Taylor expansion on such a recovery rate function, to produce a reliable result, we need to choose the order number N beyond the magnitude of recovery intensity $\lambda(t) = \exp(\alpha + \beta X(t))$, which is impossible to numerically determine.

[27] In our sample, only 72 of 272 banks recovered within two years, which corresponds to an average recovery intensity $\bar{\lambda}$ of about 0.038.

where

$$A(N) = \frac{1}{N!} \exp\left[\frac{N^2\sum_{i=1}^{J} C_i^2\beta_i^2}{2} + N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha\right]. \tag{31}$$

The above process of determining the order number N_c has an intuitive explanation; that is, the above probabilities are mostly determined by the deterministic component $N\sum_{i=1}^{J}\beta_i(\kappa_i\theta_i + (1-\kappa_i)X_i(T)) + N\alpha$, whereas the noise component $\frac{N^2\sum_{i=1}^{J} C_i^2\beta_i^2}{2}$ only contributes a small correction. When the latter noise component becomes important, the expansion series should be truncated.

References

Anari, A., Kolari, J., Mason, J., 2005. Bank asset liquidation and the propagation of the US Great Depression. In: Journal of Money, Credit and Banking 37, 753–773.
Barber, B.M., Lyon, J.D., 1997. Detecting long-run abnormal stock returns: the empirical power and specification of test statistics. Journal of Financial Economics 43, 341372.
Bayazitova, D., Shivdasani, A., 2012. Assessing TARP. Review of Financial Studies 25, 377–407.
Bernanke, B.S., 1983. Nonmonetary effects of the financial crisis in the propagation of the Great Depression. American Economic Review 73, 257–276.
Brav, A., Gompers, P.A., 1997. Myth or reality? The long-run underperformance of initial public offerings: evidence from venture and nonventure capital-backed companies. Journal of Finance 52, 17911821.
Brav, A., Gczy, C., Gompers, P.A., 1995. Underperformance of Seasoned Equity Offerings Revisited. Working paper, Harvard University.
Broome, L.L., 2011. The Dodd–Frank act: TARP bailout backlash and too big to fail. North Carolina Banking Institute Banking Journal 15, 69–81.
Cadman, B., Carter, M.E., Lynch, L.J., 2012. Executive compensation restrictions: do they restrict firms' willingness to participate in TARP? Journal of Business Finance and Accounting 39, 997–1027.
Cole, R.A., Gunther, J.W., 1995. Separating the likelihood and timing of bank failure. Journal of Banking and Finance 19, 1073–1089.
Cole, R.A., Wu, Q., 2009. Predicting Bank Failures Using a Simple Dynamic Hazard Model. Working paper, Depaul University and the University of Newcastle.
Contessi, S., Francis, J.L., 2011. TARP beneficiaries and their lending patterns during the financial crisis. Federal Reserve Bank of St. Louis, Review 93, 105–125.
Cornett, M.M., Li, L., Tehranian, H., 2013. The performance of banks around the receipt and repayment of TARP funds: over-achievers versus under-achievers. Journal of Banking and Finance 37, 730–746.
Duchin, R., Sosyura, D., 2012. The politics of government investment. Journal of Financial Economics 106, 24–48.
Duffie, D., Saita, L., Wang, K., 2007. Multi-period corporate default prediction with stochastic covariates. Journal of Financial Economics 83, 635–665.
Duffie, D., Eckner, A., Horel, G., Saita, L., 2009. Frailty correlated default. Journal of Finance 64, 2089–2123.
Fama, E.F., 1998. Market efficiency, long-term returns and behavioral finance. Journal of Financial Economics 49, 283306.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.
Fama, E.F., French, K.R., 1993. The cross-section of expected returns. Journal of Financial Economics 33, 3–56.
Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. Journal of Finance 50, 131–156.
Farruggio, C., Michalak, T., Uhde, A., 2013. The light and dark side of TARP. Journal of Banking and Finance 37, 2586–2604.
Feldman, R., Schmidt, J., 1999. What are CAMELS and Who Should Know? Federal Reserve Bank of Minneapolis, Fedgazetter.
Flannery, M., Kwan, S., Nimalendran, M., 2004. Market evidence on the opaqueness of banking firms' assets. Journal of Financial Economics 71, 419–460.
Ghosh, S., Mohamed, S., 2010. The Troubled Asset Relief Program (TARP) and its limitations: an analysis. International Journal of Law and Management 52, 124–143.
Hoshi, T., Kashyap, A.K., 2010. Will the US bank recapitalization succeed? Eight lessons from Japan. Journal of Financial Economics 97, 398–417.
Jaffe, J.F., 1974. Special information and insider trading. Journal of Business 47, 410428.
Jordan, D.J., Rice, D., Sanchez, J., Wort, D.H., 2010. Taking TARP Funds can be Hazardous to Your Bank's Wealth. Working paper, University of California, Golden Gate University, Bank of the West, and California State University, East Bay.
Kim, W.Y., 2010. Market Reaction to Limiting Executive Compensation: Evidence from TARP Firms. Working paper, Dickinson College.
Kim, D.H.., Stock, D., 2012. Impact of TARP financing choice on existing preferred stocks. Journal of Corporate Finance 18, 1121–1142.
King, M.R., 2009. Time to Buy or Just Buying Time? The Market Reaction to Bank Rescue Packages. Working paper no. 288, Bank for International Settlements, Switzerland.
Kothari, S.P., Warner, J.B., 1997. Measuring long-horizon security price performance. Journal of Financial Economics 43, 301340.
Li, L., 2012. TARP Funds Distribution and Bank Loan Supply. Working paper, University of Kansas.
Loughran, T., Ritter, J., 1995. The new issues puzzle. Journal of Finance 50, 2352.
Lyon, J.D., Barber, B.M., Tsai, C., 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 54, 165–201.
Mandelker, G., 1974. Risk and return: the case of merging firms. Journal of Financial Economics 1, 303336.
Martin, D., 1977. Early-warning of bank failure: a logit regression approach. Journal of Banking and Finance 1, 249–276.
Meyer, P.A., Pifer, H.W., 1970. Prediction of bank failures. Journal of Finance 25, 853–868.
Mitchell, M.L., Stafford, E., 2000. Managerial decisions and long-term stock price performance. Journal of Business 73, 287–329.
Morgan, D.P., 2002. Rating banks: risk and uncertainty in an opaque industry. American Economic Review 92, 874888.
Ng, J., Vasvari, F.P., Wittenberg-Moerman, R., 2010. The Participants in the TARP Capital Purchase Program: Failing or Healthy Banks? Working paper, Massachusetts Institute of Technology, London Business School, and University of Chicago.
Partington, G., Kim, M.H., 2008. Modeling Bankruptcy Prediction using Cox Regression Model with Time-Varying Covariates. Working paper, University of Sydney, Australia.
Shimizu, K., 2006. How can we effectively resolve the financial crisi: empirical evidence on the bank rehabilitation plan of the Japanese government. Pacific-Basin Finance Journal 14, 119–134.
Shumway, T., 2001. Forcasting bankruptcy more accurately: a simple hazard model. Journal of Business 74, 101–124.
Sinkey Jr., J.F., 1979. Problem and Failed Institutions in the Commercial Banking Industry. JAI Press, Greenwich, CT.
Song, W.-L., Uzmanoglu, C., 2011. Systemic Risk Channel and TARP: Banking Relationship Spillover in the Credit Default Swap and Stock Markets. Working paper, Louisiana State University.
Taliaferro, R., 2009. How Do Banks Use Bailout Money? Optimal Capital Structure, New Equity, and the TARP. Working paper, Harvard Business School.
Thomson, J.B., 1991. Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland. Economic Review Quarter 1, 9–20.
Veronesi, P., Zingales, L., 2010. Paulson's gift. Journal of Financial Economics 97, 339–368.
Whalen, G., 2005. A Hazard Model of CAMELS Downgrades of Low-Risk Community Banks. Economics working paper 2005-1, Office of the Comptroller of the Currency.
Wheelock, D.C., Wilson, P.W., 2000. Why do banks disappear? The determinants of US bank failures and acquisitions. Review of Economics and Statistics 82, 127–138.
Wilson, L., Wu, Y.W., 2012. Escaping TARP. Journal of Financial Stability 8, 32–42.
Wilson, L., 2013. TARP's deadbeat banks. Review of Quantitative Finance and Accounting (forthcoming).