The Role of Relative Performance in Bank Closure Decisions*

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This paper studies a banking industry subject to common and idiosyncratic shocks. We compare two types of regulatory closure rules: (1) an "absolute closure rule," which closes banks when their asset–liability ratios fall below a given threshold, and (2) a "relative closure rule," which closes banks when their asset–liability ratios fall sufficiently below the industry average. There are two main results: First, relative closure rules imply forbearance during "bad times," defined as adverse realizations of the common shock. This forbearance occurs for incentive reasons, not because of irreversibilities or political economy considerations. Second, relative closure rules are less costly to taxpayers, and these savings increase with the relative variance of the common shock. To evaluate the model, we estimate a panel-logit regression using a sample of U.S. commercial banks. We find strong evidence that U.S. bank closures are based on relative performance. Individual and average asset– liability ratios are both significant predictors of bank closure.

1. Introduction

A critical component of any bank regulatory package concerns the timing of bank closures, i.e., when exactly should regulators close or forcibly merge a bank? While other policies, like auditing, capital requirements, and deposit insurance are designed to contain risks, nevertheless bank failures do occur. By the principle of backward induction, how and under what circumstances banks expect closure has important consequences for how they behave before they are closed. An efficient closure policy should account for these incentive effects.

The goal of this paper is to study the incentive effects of bank closure policy. In doing so, we abstract from all other aspects of bank regulation, not only for analytical convenience but also because our goal is rather modest. We do not attempt to formulate a set of incentive-compatible policies that implement an informationally constrained Pareto optimum. We merely want to compare the cost effectiveness, in terms of expected taxpayer liability, of alternative closure rules. We can do this without taking a stand on exactly what banks do, or should be doing. Instead, we just consider two general

*We thank Simon Kwan and Mark Levonian for helpful comments. Laura Haworth and Hiroshi Kokame provided excellent research assistance. Opinions expressed do not necessarily reflect the views of the Federal Reserve Bank of San Francisco or the Board of Governors of the Federal Reserve System. types of rules which are simple, transparent, and pragmatic. Both rules are designed to elicit the same response (i.e., risk) by banks. Given this, we can then ask the following question: For any desired level of bank risk, which closure rule is less costly?¹

There are two key inputs to our analysis. The first is the assumption that banks are subject to both common and idiosyncratic shocks. Interest rate fluctuations are one example of a common banking shock. The second key input is the assumption that regulators are unable to monitor bank portfolio decisions perfectly.

Since bank actions are unobserved, closure policy must be based on ex post realized outcomes. This confronts the regulator with a signal extraction problem. For incentive reasons, an efficient policy should attempt to distinguish between banks that are in trouble as a result of their own actions (i.e., moral hazard), and banks that were simply unlucky. While a policy of "prompt corrective action" can indeed discourage moral hazard and save taxpayer money, it can also cause banks to be unduly cautious in the presence of idiosyncratic shocks. Alternatively, separating moral hazard from bad luck

^{1.} There are studies that explore the interaction between bank closure policy and other policy instruments. For example, Acharya and Dreyfus (1989) study the potential complementarities between deposit insurance pricing and bank closure policy. However, they assume symmetric information and focus their analysis on dynamics and timing issues, while we focus on moral hazard and incentives.

can achieve the same overall level of banking industry risk at a lower (expected) cost to the taxpayer.²

We show that the key to separating moral hazard from bad luck is to base closure decisions on relative performance. With a large number of ex ante identical banks, relative performance is a good indicator of relative "effort."³ Consequently, a rule that closes banks whenever their asset–liability ratios fall below the average of a cross-section of comparable banks by a given amount is superior to one based solely on each individual bank's asset–liability ratio.⁴ An interesting implication of a relative closure rule is that it leads to forbearance during "bad times," defined as adverse realizations of the common shock. It is important to realize, however, that this forbearance occurs solely for ex ante incentive reasons, not because of irreversibilities or political economy considerations.⁵

In fact, if he could, our regulator would like to renege ex post on the announced relative closure rule once the bank's portfolio decision was made. The regulator would like to close unlucky banks in order to keep them from "gambling for resurrection." However, this finite-horizon time consistency problem would be mitigated in a repeated framework. In a repeated game, regulators would have an incentive to follow through on their announced closure policies if failing to do so would lead to loss of future credibility.⁶ Moreover, legal and institutional constraints (e.g., the Federal Deposit Insurance Corporation Improvement Act of 1991 or FDI-CIA), even when they contain generous opt-out agreements, undoubtedly provide some degree of commitment.

We are not the first to point out the potential incentive benefits of a relative closure rule for moral hazard reasons. Nagarajan and Sealey (1995) also make this point. Our contribution is to formulate the problem in a way that leads to empirically testable predictions. We do this by explicitly modeling a large number of banks subject to continuously distributed shocks and by basing our closure rule on the cross-sectional average asset–liability ratio, as opposed to some notion of a "market return." One way to think of the difference between these two approaches is that our regulator is more concerned with accounting information, while the regulator in Nagarajan and Sealey's paper is more concerned with stock prices.⁷

Other arguments against constant regulatory rules have been made in the literature. Blum and Hellwig (1995) argue that capital adequacy regulations can reinforce macroeconomic fluctuations. In their model, economic downturns reduce the quality of bank balance sheets. Because their regulatory constraints are now more binding, banks respond by reducing their lending, exacerbating the economic downturn. A relative closure rule would mitigate this problem by easing the regulatory constraints faced by banks in aggregate downturns.

Other arguments have been made on the basis of reducing resolution costs. Acharya and Yorulmazer (2007, 2008) generate countercyclical forbearance based on the ex post cost of resolution of failed banks. In their model, acquisition of failed banks by surviving banks is posited to result in lower resolution costs than liquidating the failed bank's assets. As it becomes more difficult to find surviving banks to acquire failed banks in environments with higher numbers of bank failures, they find that the cost of closing a failed bank increases with the number of bank failures, a phenomenon they describe as "too-many-to-fail."

Arguments have also been made that there may be "contagion" in failures across the banking system. Diamond and Rajan (2005) describe an environment in which bank closures may lead to adverse spillovers as they reduce the liquidity of the banking system. Their model also suggests that proper time-varying regulatory rules can mitigate the costs of resolving bank failures. Lang and Stulz (1992) demonstrate that bankruptcy announcements lead to adverse valuations of industry competitors, suggesting that closures of failed banks could lead to reduced confidence in other banks in the system.

More generally, our results relate to the literature on optimal bankruptcy procedures and the evaluation of Chapter 11 proceedings. For example, Baird (1991) argues that Chapter 11 protection can encourage managers to initiate bankruptcy procedures, and Mooradian (1994) argues that Chapter 11 protection may serve as a mechanism for achieving a sepa-

^{2.} One issue that has attracted attention in the literature is the limits to government information. Some have argued (e.g., Berger, Davies, and Flannery 2000, Flannery 1998) that private sector information could be superior in certain situations. To the extent that this is true, regulators would also want to incorporate the private information concerning relative performance in the manner modeled below.

^{3.} The advantages of relative performance contracts were first discussed in the labor literature. See, e.g., Lazear and Rosen (1981) or Nalebuff and Stiglitz (1983). It should be noted that, while our model presumes ex ante identical banks, our empirical work attempts to control for one potentially important source of heterogeneity, namely, size.

^{4.} One might wonder whether such a rule would be consistent with the dictates of FDICIA, which calls for "prompt corrective action" and contains no explicit reference to relative performance. However, as discussed in more detail by Mailath and Mester (1994), FDICIA also directs regulators to resolve troubled banks in the *least costly way* and grants regulators a large degree of discretion in deciding how to do this.

^{5.} Kane (1989) discusses forbearance based on regulatory malfeasance. Demirgüç-Kunt (1991) and Fries, Mella-Barral, and Perraudin (1997) analyze forbearance based on irreversibility and the resulting option value of waiting. Boot and Thakor (1993) base forbearance on a principal– agent problem between the bank regulator and the taxpayer.

^{6.} See Mailath and Mester (1994) for a detailed analysis of the time consistency problem in bank closure policy.

^{7.} In a later paper, Nagarajan and Sealey (1998) extend their framework to a setting of adverse selection as well as moral hazard, although in it they only focus on the pricing of deposit insurance, not on bank closure policy.

rating equilibrium, by making it prohibitively costly for inefficient firms to mimic efficient ones in debt restructurings, while Aghion, Bolton, and Fries (1999) argue that strict bank closure policies can discourage managers from truthfully disclosing their bank's asset position.⁸

There is relatively little empirical evidence concerning whether time-varying closure rules have been used by regulators. Thomson (1991) examines the determinants of bank closure during the 1980s. He finds that various measures of macroeconomic conditions are usually significant predictors of bank failure. Brown and Dinç (2006), examine bank failures among 21 emerging market economies in the 1990s. Their results suggest that conditions in the rest of the banking sector are incorporated into the regulatory closure decision in a manner consistent with the predictions of the model in this paper.

Below, we estimate a panel-logit regression using a sample of annual data for over 12,000 U.S. commercial banks during the period 1992 through 1997, which corresponds to the post-FDICIA period in which failures were relatively prevalent. We find strong evidence that U.S. bank closures are based on relative performance. Our results demonstrate that both individual and average asset—liability ratios for a bank's home state are significant predictors of bank closure, and the coefficient estimates are consistent with this theory. Moreover, the results are robust to the exclusion of small banks from the sample, as well as to the inclusion of other controlling variables. Overall, we conclude that relative performance has been an input to bank closure decisions.

Our paper is organized as follows. Section 2 discusses our model. Section 3 describes the controlling variables we use and our results. Section 4 concludes. An appendix provides the proofs of our propositions.

2. A Simple Model of Bank Closure

2.1. Bank Investment Decision

We begin with a very simple model of bank closure. We assume that there are an infinite number of homogenous banks of measure zero. We model a representative bank *i*, which decides the amount of "effort," μ_i , to invest in enhancing the quality of its asset portfolio, where possible chosen values of μ range between the positive finite values min(μ) and $\max(\mu)$.⁹ The cost of supplying an amount of effort equal to μ is assumed to satisfy the function $V(\mu)$, where $V_{\mu} > 0$ and $V_{\mu\mu} > 0$. For simplicity, we assume that effort costs are borne up front. This simplifies the analysis by making this cost independent of the probability of bankruptcy, but this assumption drives none of our results. Finally, we assume that the optimal effort choice μ^* is always interior.

There are two shocks: a common shock, θ , which affects all banks, and an idiosyncratic shock, ε_i , which falls on bank *i* alone.¹⁰ We assume that ε_i and θ are distributed on the intervals $[\underline{\varepsilon}, \overline{\varepsilon}]$ and $[\underline{\theta}, \overline{\theta}]$, respectively.

The model has one period, although our analysis extends to the repeated case if shocks are independently and identically distributed (i.i.d.). The timing of the model is as follows: First, the regulator announces a closure rule. Next, the bank chooses its effort level, μ_i . At the end of the period, the shocks are realized and the value of bank assets minus liabilities are determined, which we define as A_i . We assume that A_i satisfies

(1)
$$A_i = \mu_i + \theta + \varepsilon_i.$$

Finally, the regulator makes its closure decision consistent with its announced rule.

To make the model interesting, we assume the regulator only observes the total value of A_i , not the values of its components. We therefore limit the regulator to closure rules conditional on A_i . Moreover, as we noted in the introduction, we assume that the regulator can commit to a closure rule. Later we discuss the implications of constraining the regulator to time-consistent rules.

Banks are assumed to have limited liability, having zero value under bankruptcy. As in Marcus (1984), we assume that if the bank is allowed to continue, it has a charter value. We allow the charter value, $C(\mu_i)$ to be increasing in current bank effort. The charter value represents the expected future profits from continued banking operations.

Define ε^* as the minimum realization of ε_i under which the regulator chooses to allow the bank to continue in operation. Clearly, ε^* will depend on the regulator's closure rule. Because regulators are constrained to follow closure rules based on A_i , their observable indicator of bank financial health, ε^* will in practice be the level of ε_i that yields the minimum value of A_i that does not result in closure. For now,

^{8.} The literature on the merits of Chapter 11 proceedings is mixed. Strict closure rules can provide managerial discipline, so that Chapter 11 protection of borrowers may exacerbate moral hazard problems (Gertner and Scharfstein 1991, Weiss and Wruck 1998). However, Chapter 11 protection may yield benefits when contracting technology is limited (Aghion and Bolton 1992, Hart and Moore 1998, Berkovich, Israel, and Zender 1998, and Harris and Raviv 1995).

^{9.} Similar frameworks for studying bank regulation can be found in Dewatripont and Tirole (1993) and Giammarino, Lewis, and Sappington (1993).

^{10.} We do not model the lending choices of banks directly. In particular, we do not allow banks to manipulate the relative importance of common and idiosyncratic shocks to their portfolios. The literature has expressed some concern that banks will respond to countercyclical forbearance policies by adjusting their portfolios to give less weight to idiosyncratic shocks (e.g., Goodhart, et al. 1998 and Acharya and Yorulmazer 2007).

we note that for all the closure rules we entertain below, ε^* is a decreasing function of both bank effort μ_i and the common shock θ , since A_i is increasing in both of these arguments.

The representative bank's investment decision is to choose μ_i to maximize expected bank value net of effort cost, which is

(2)
$$\int_{\underline{\theta}}^{\overline{\theta}} \left[\int_{\varepsilon^*}^{\overline{\varepsilon}} \left[A_i + C(\mu_i) \right] f(\varepsilon) d\varepsilon \right] g(\theta) d\theta - V(\mu),$$

where $f(\cdot)$ is the density of ε and $g(\cdot)$ is the density of θ . The bank's first-order condition satisfies

(3)
$$\int_{\underline{\theta}}^{\overline{\theta}} \left[\int_{\varepsilon^*}^{\overline{\varepsilon}} (1+C_{\mu}) f(\varepsilon) d\varepsilon - \left(\frac{\partial \varepsilon^*}{\partial \mu_i} \right) (\mu_i + \theta + \varepsilon^* + C) f(\varepsilon^*) \right] g(\theta) d\theta = V_{\mu}.$$

The two arguments on the left-hand side of equation (3) represent the marginal benefits of additional effort. The first term reflects the increased expected payoff in nonbank-ruptcy states, holding the probability of bankruptcy constant. The second term reflects the value of the change in the probability of bankruptcy that results from a marginal change in effort.

2.2. Case 1: Regulatory Standard Based on Absolute Performance

We first consider a closure rule based solely on absolute bank performance. Suppose that a bank is closed if

$$(4) A_i \leq m,$$

where m = 0 is obviously a special case where banks are closed on insolvency.

Define μ_i^p as the privately optimal choice of effort made by an individual bank given the absolute closure rule. Alternatively, define μ_i^s as the socially optimal level of effort, the one that maximizes the expected stream of revenues from the bank plus bank charter value, net of effort costs, and includes the expected regulatory liabilities under insolvency. We show in the appendix that $\mu_i^p \leq \mu_i^s$. This is our first result:

PROPOSITION 1: With a closure rule based on insolvency, the level of privately chosen bank effort is below that consistent with maximizing the total "social revenue stream."

Proposition 1 derives from the standard moral hazard result with limited liability: Since its losses are bounded from below, the private bank chooses a lower level of effort because it does not share in the gains to returns in bankruptcy states. These instead accrue to the regulator as a reduction in tax liabilities.

2.3. Case 2: Regulatory Standard Based on Relative Performance

Next, we assume the regulator bases closure on relative performance. Before showing how this can enhance efficiency, we should emphasize that for simplicity we allow the bank to alter the mean of its net asset position, but not its variance. If banks can also (independently) choose the variance of their net asset positions then relative performance schemes can produce bad equilibria, in which contestants choose very risky actions and low effort levels.

For example, Hvide (2002) shows that if effort is costly but risk-taking is not, then it will be optimal for the contestants to choose maximally risky outcome distributions with very low effort. Intuitively, injecting a lot of variance into the outcome reduces the marginal benefit of effort, since the noise is so great, which then permits low effort levels to be sustained in equilibrium. This is optimal if effort is costly but risktaking isn't. Alternatively, the literature has expressed some concern that banks will respond to tournaments by adjusting their portfolios to give less weight to idiosyncratic shocks (e.g., Goodhart, et al. 1998). In both of these cases, the importance of adjustment of overall variance or the weight on idiosyncratic vs. common shocks will be dependent on the costliness to the bank of making such an adjustment. When such adjustments are costly, it is unlikely that much adjustment would take place in an uncoordinated environment.

We assume that there are a large number of banks, so that the law of large numbers yields,

(5)
$$\theta = \overline{A} - \overline{\mu},$$

where \overline{A} and $\overline{\mu}$ are the cross-sectional average levels of bank asset positions and efforts, respectively. By equations (1) and (5), and since $E(\varepsilon_i) = 0$,

(6)
$$E(\mu_i - \overline{\mu}) = A_i - \overline{A}.$$

By incorporating relative performance, then, the regulator can infer relative effort. We therefore posit a relative closure rule which satisfies¹¹

(7)
$$A_i - \overline{A} \leq n$$
,

where $\varepsilon \leq n \leq \overline{\varepsilon}$.

We solve for the equilibrium level of bank effort under this closure rule in the appendix.

Note that our model does not allow banks to manipulate the relative importance of common and idiosyncratic shocks to their portfolios. While the literature has expressed some

^{11.} The fact that the benchmark can be taken as the mean, rather than some more general weighting, depends on our homogeneity assumption. If banks differed by size or idiosyncratic risk, then it would no longer be optimal to use the mean as a benchmark. See, e.g., Holmstrom (1982, p. 337).

concern that banks will respond to tournaments by adjusting their portfolios to give less weight to idiosyncratic shocks (e.g., Goodhart, et al. 1998), it is difficult to see how such coordinated action could be sustained in a competitive banking system.

To allow for a common basis of comparison, we first find the relative closure rule which elicits the same level of effort as the absolute closure rule. We then compare the expected liability of the regulatory institution under the two closure rules. We designate as preferable the rule that delivers a given level of bank effort with the lowest expected regulatory liability.

To obtain analytic solutions for the regulator's expected liability, we must put more structure on the distribution of ε_i . Accordingly, without essential loss of generality we assume from here on that ε_i is distributed uniformly on the interval $[\varepsilon, \overline{\varepsilon}]$ with density *f*.

Define A^m and A^n as the minimum realizations of A_i necessary to avoid closure under the absolute and relative closure rules, respectively. We demonstrate in the appendix that

(8)
$$A^n - A^m = \theta - \mathbf{E}(\theta).$$

This leads to our second result:

PROPOSITION 2: For a given level of bank effort, closure takes place at higher (lower) levels of A_i under the relative closure rule than under the absolute closure rule when θ exceeds (falls short of) its expected value.

Intuitively, the proposition states that the relative closure rule will be more stringent in good times, i.e., when the common shock θ is above its mean, and more lenient in bad times.

Note that the implied "forbearance" has nothing to do with the opportunity cost of irreversibly shutting down banks, or with regulatory malfeasance. Rather, forbearance is advantageous here solely for ex ante incentive reasons. Basing closure on relative performance allows the regulator to more accurately separate those banks choosing low effort levels from those banks that are unlucky. If a bank knows its effort level is likely to be detected and incorporated in the regulator's closure decision, it will choose a higher level of effort.

Finally, we turn to the relative liability of the bank regulator. Define L_m as the expected liability of the regulatory institution under the absolute closure policy that elicits level of effort $\hat{\mu}$. L_m satisfies¹²

(9)
$$L_m = -\int_{\underline{\theta}}^{\overline{\theta}} \int_{\underline{\varepsilon}}^{\varepsilon^*} A_i(\widehat{\mu}, \theta, \varepsilon_i) f(\varepsilon_i) d\varepsilon_i g(\theta) d\theta.$$

Define L_n as the expected liability of the regulatory institution under the relative closure policy that elicits the same level of effort ($\hat{\mu}$). Substituting for ε^* as above, L_n satisfies

(10)
$$L_n = -\int_{\underline{\theta}}^{\overline{\theta}} \int_{\underline{\varepsilon}}^n A_i(\widehat{\mu}, \theta, \varepsilon_i) f(\varepsilon_i) d\varepsilon_i g(\theta) d\theta.$$

Assuming that ε_i is distributed uniformly, we demonstrate in the appendix that

(11)
$$L_m - L_n = \frac{1}{2} \left[\frac{Var(\theta)}{\overline{\varepsilon} - \underline{\varepsilon}} \right]$$

This leads to our third result:

PROPOSITION 3: For closure rules that elicit the same level of bank effort, the relative closure rule has a smaller expected liability to the bank regulator than the absolute closure rule. Moreover, the cost advantage of the relative closure rule is increasing in the variance of the common shock and decreasing in the variance of the idiosyncratic shock.

Note that this cost advantage implies that sustaining a relative closure rule is valuable to the regulator. In a repeated context, a standard trigger strategy argument can be used to show that concerns about losing these benefits in the future can induce a discretionary regulator to comply with the relative closure rule ex post.

3. Empirical Results

3.1. Estimation Method

In this section, we investigate whether relative performance matters for bank closure decisions in the United States. Based on our theoretical model above, we formulate a binary choice model in which the regulator chooses at each point in time either failure or continuation of operations.

The definitions and sources for all variables used in this study are listed in Table 1. We represent the regulator's binary choice as a random variable *FAIL*, which takes the value one if the regulator chooses failure and the value zero if the bank is allowed to continue. Failure is defined as the end of a bank's existence whose resolution is arranged by the FDIC or other regulatory agency.

Our base specifications come directly from the theoretical model above. As a benchmark for relative performance, we consider the average financial position of banks in the home state of bank *i* in period *t*, \overline{A}_{jt} , where *j* denotes the home state of bank *i*. The base absolute closure rule then specifies closure decisions as depending solely on a bank's current asset position, A_{ijt} , while our base relative closure rule specifies that closure decisions also depend on the average financial position of banks in the home state of bank *i* in period *t*, \overline{A}_{jt} .

^{12.} Note that we do not consider the loss of bank charter value as part of the closure cost. The inclusion of charter loss would not change the results systematically with either closure rule.

TABLE 1 VARIABLE DEFINITIONS

FAIL	Binary variable which takes the value 1 when a bank fails and the value 0 when a bank is allowed to continue. Failure occurs when an entity ceases to exist and its resolution was arranged by the Federal Deposit Insurance Corporation, Resolution Trust Corporation, National Credit Union Administration, or state or other regulatory agency.
A_{iji}	Book value of total assets divided by book value of total liabilities of bank i in state j at time t . Total assets exclude loan loss reserves. Total liabilities exclude subordinated debt.
\overline{A}_{jt}	Average value of A_{ijt} for all entities in a state in a given year.
SIZE	Book value of total assets excluding loan loss reserves.
COMMERCIAL	Commercial and industrial loans divided by total assets.
AGRICULTURAL	Loans to finance agricultural production and other loans to farmers divided by total assets.
REALESTATE	Loans secured by real estate divided by total assets.
NON-INTEREST	Total non-interest expense divided by total assets.
CD	Total time deposits of \$100,000 or more divided by total assets.
90DAYSLATE	Total loans and lease financing receivables: 90 days or more past due and still accruing divided by total assets.

Source: All data are from the Federal Reserve Bank of Chicago's Bank Condition and Income Database.

In addition to the base specifications, we add a number of conditioning variables commonly used in the literature to forecast bank closures (e.g., Wheelock and Wilson 2000). First, we introduce a variable to measure relative bank size. SIZE_{iii} is proxied by the book value of bank i in state j in period t. It is widely believed that regulators might be more hesitant to close large banks in poor financial condition because of the potential for adverse systemic results from large bank closures. Second, we introduce three proxies for sectoral exposure: COMMERCIAL_{iit} represents the share of commercial and industrial loans to total assets. AGRICULTURE_{iit} represents the share of agricultural loans as a share of total assets. REALESTATE_{iit} represents the share of total assets in the real estate sector. We also introduce NON-INTEREST_{ijt}, the ratio of non-interest expenses to total assets, as an indicator of bank efficiency. As an indicator of the composition of bank liabilities, we introduce CD_{ijt} , the ratio of time deposits exceeding \$100,000 as a share of total assets. This indicates the share of uninsured deposits. Finally, as an indicator of asset quality, we introduce 90DAYSLATE_{ijt}, total loans and receivables 90 days or more past due as a share of total assets.

We measure A_{ijt} as the book value of the asset-to-liability ratio of bank *i* in period *t*. The use of book values is consistent with the maintained hypothesis that the bank regulator has imperfect information about individual banks' financial health.¹³ Bank equity values would partially reflect the regulatory environment in which the bank operates and hence would raise simultaneity problems in our specification. Finally, asset book values are actually used by regulators in making closure decisions. The average financial position of banks in period *t* is represented by \overline{A}_{jt} , the cross-sectional mean value of the book asset–liability ratios of banks in the home state of bank *i* in period *t*.

The following binary model then nests both the absolute and relative closure rules, as well as the conditioning variables discussed above:

(12)
$$\Pr(F=1)_{iit} = \gamma_t + \beta_1 A_{ijt} + \beta_2 \overline{A}_{jt} + \beta_3 \xi_{ijt} + e_{ijt},$$

where γ_t represents a time dummy for period t, ξ_{ijt} is the vector containing the conditioning variables listed above, and e_{ijt} represents an i.i.d. disturbance term.¹⁴ A prediction of the structural model above is that $\beta_1 = -\beta_2$.

3.2. Data

The data set used in this study consists of a panel of annual data for 12,303 U.S. commercial banks from 1992 through 1997. We chose the starting date because, following FDICIA, a relatively homogenous regulatory environment has existed.¹⁵ We choose the ending date because subsequent to 1997 years exist in which no failures take place. All data for individual banks were acquired from the Federal Reserve Bank of Chicago's Bank Condition and Income Database.

Because banks both fail and come into existence over the course of our sample, the panel is not balanced. However, this should not lead to biases in the data because the missing

^{13.} Book values are likely to measure the financial positions of banks with errors. However, market measures were unavailable due to the extremely small number of bank failures among banks that issue equity. Indeed, it appears clear that a sample of equity-issuing banks would have a selection bias towards healthy banks.

Concerning the issue of errors in variables, both A_{ijt} and \overline{A}_{jt} are likely to be measured with error. De Varo and Lacker (1995) demonstrate that the net effect in this case is still some attenuation towards zero.

^{14.} As no failures occurred in 1996 or 1997, to avoid perfect multicollinearity we do not include time dummies for these years.

^{15.} While FDICIA was only formally passed by the United States Congress in December of 1992, it is clear that these reforms were already being incorporated in the closure decisions of bank regulators throughout the year. Indeed, the 1991 data also seem to reflect the stricter regulatory activity called for under FDICIA, although we left this year out of our reported sample to limit ourselves to the post-FDICIA period.

variables due to entry or random exit (as in the case of an unassisted merger) are likely to be uncorrelated with the error term in our model. In the case where observations are missing because of bank failure, the reason for the missing data is precisely what we are attempting to identify in our model specification.

Summary statistics for the data are shown in Table 2. Our data set includes 113 bank failures over the 1992–1997 period. Because the number of failures in our sample is very small relative to the number of nonfailures, we use a logit specification in all our analysis. The logit specification is insensitive to uneven sampling frequency problems (Maddala 1983).

Two patterns stand out in the data. First, the average assetto-liability ratio of the banking sector increases over the sample, implying an increase in the overall health of the banking system. Unsurprisingly, the number of bank failures diminishes over the panel, reflecting this increase in the financial system's overall health. The year 1992 is particularly active for bank failures, primarily reflecting closures associated with the new tighter regulatory policies under FDICIA. However, even excluding 1992 it is clear that the number of bank failures diminishes over the sample. To rule out time-specific effects in the data stemming from these trends, we include time dummies, γ_t , in our specifications.¹⁶

We conduct a preliminary investigation of the relationship between bank closure and local conditions in Table 3. We divide the observations in our sample into six subsamples, based on the value of local conditions at time t, or \overline{A}_{jt} . In particular, we separate the observations into six groups between 0 and 1, 1 and 2, and greater than 2 standard deviations from either side of the sample mean value of \overline{A}_{jt} . We then investigate the probability of bank closures given a potentially closed bank. For our purposes, we consider banks with values of A_{ijt} between 1.00 and 1.05.¹⁷ This range includes all of the failed banks in our sample.

For the subsample with below-average local conditions, the relationship between local conditions and the probability that a bank within the critical range was closed is monotonic: 7.84 percent of banks in the critical range within the subsample with the poorest local conditions (more than two standard deviations below the mean) were closed, 13.89 percent of the banks in the critical range in the next higher sub-

TABLE 2	
SUMMARY	STATISTICS

Year	\overline{A}_{jt}	# of bank failures	Avg. value of A_{ijt} for failed banks
1992	1.103	70	1.023
1993	1.109	26	1.018
1994	1.110	9	1.039
1995	1.119	4	1.007
1996	1.123	4	1.013

Source: Federal Reserve Bank of Chicago, Bank Condition and Income Database.

sample were closed, and 16.06 percent of the banks in the next higher subsample were closed. However, the monotonicity breaks down for banks experiencing above-average conditions, as only 11.34 percent of the banks with local conditions between the sample mean value and one standard deviation above the mean were closed. The next higher category obtains a 25 percent figure, resuming the monotonic pattern. However, as there are only four failures within that subsample with local conditions more than one standard deviation above average, one would not draw much of an inference from this observation.

Overall, the results in Table 3 do suggest that regulators are more likely to close a bank of a given asset position the stronger are local conditions, although the results appear to be strongest for substandard local conditions. Nevertheless, it is when times are bad that we would expect regulatory forbearance to be most prominent. In the following section, we formally test this hypothesis for the full sample.

3.3. Results

The results for logit estimation of the entire sample are listed in Table 4. The first and second columns report the results for the base absolute and relative closure rule specifications, respectively. Absolute bank performance, A_{ijt} , enters significantly with its predicted negative sign in both specifications. However, the coefficient estimate on absolute bank performance is sensitive to the inclusion or exclusion of a relative performance measure. In the specification including relative performance, its value almost doubles.

The mean industry performance measure included in the second column, \overline{A}_{jt} is also highly significant. Moreover, its value is of the opposite sign and of the same order of magnitude as the coefficient estimate on A_{ijt} . The formal theory above predicts that these coefficients would be of equal and opposite sign, but we do not find that to be the case. We conducted likelihood ratio and Wald tests of this restriction, and both were strongly rejected. Nevertheless, the similarity

^{16.} Because there are no failures in 1997, we are forced to drop two of the time dummies, one of which must be 1997, to allow for estimation. We include dummies for 1992 through 1995 in the specifications, which yielded the results reported in Tables 3 and 4. Our results were not sensitive to which time dummies were included. Estimates of the coefficients on these time dummies, as well as those for specifications including alternative time dummies, are available from the authors upon request.

^{17.} The qualitative results were robust to minor perturbations around this range.

Subsample	(1)	(2)	(3)	(4)	(5)	(6)
Percent of failures	7.84	13.89	16.06	11.34	25.00	
With $1.00 < A_{ijt} < 1.05$						
# of banks	2,216	3,596	23,207	34,359	5,979	1,977
# of failures	11	6	76	16	4	0
Values of \overline{A}_{jt} in subsample range	<1.093	1.093-1.102	1.102–1.110	1.110–1.119	1.119–1.127	>1.127

TABLE 3
CLOSURES OF BANKS AND LOCAL CONDITIONS

Note: Subsamples are based on home-state conditions of bank A_{ijt} at time *t*. Subsample 1 contains observations with \overline{A}_{jt} more than 2 standard deviations lower than the mean of the entire sample. Subsample 2 contains observations with \overline{A}_{jt} between 1 and 2 standard deviations below the mean, subsample 3 between 0 and 1 standard deviations above the mean, subsample 4 between 0 and 1 standard deviations above the mean, subsample 5 between 1 and 2 standard deviations above the mean, and subsample 6 more than 2 standard deviations above the mean.

in the magnitudes of these coefficients is supportive of the model above.

Comparing the base specifications, all of the regression diagnostics strongly favor the relative closure rule specification. Adding \overline{A}_{jt} to the specification reduces the Akaike Information Criteria (AIC) statistic from 1,253.6 to 951.3. Similarly, the second specification lowers the Schwartz criterion from 1,298.9 to 1,005.6 and the -2 log-likelihood from 1,243.6 to 939.3. Likelihood ratio tests strongly reject the restriction that the coefficient on \overline{A}_{jt} is equal to zero at a 1-percent confidence level.

The relative rule specification also does a much better job of predicting bank failures. Under the rule that a bank failure is predicted for probability values greater than or equal to 50 percent, the absolute specification with all of the conditioning variables predicts only six of the 113 bank failures in the sample. In contrast, the relative rule predicts 13 of the 113 bank failures correctly.

The third and fourth columns add the $SIZE_{ijt}$ variable to both specifications. A "too big to fail" theory of bank closure policy would suggest a negative coefficient on this variable, as regulators would resist closing large banks due to systemic concerns. While size does have the predicted negative coefficient estimate, it fails to achieve statistical significance in either specification, a disappointing performance in such a large sample. It may be that the impact of too-big-to-fail protection is nonlinear, such that bank size is only relevant after banks become large enough that their failures would threaten the stability of the payments system.

More importantly for our purposes, our base specification results are robust to the consideration of bank size. A_{ijt} and \overline{A}_{jt} enter in the presence of a bank size variable with quite similar coefficient estimates as they obtained in the base specifications. Both are again highly significant and consistent with the prediction of the theory. Again, the diagnostic and classification statistics strongly support the relative closure rule specification over a simple absolute closure rule, although there is little improvement from the inclusion of the $SIZE_{ijt}$ variable. For the relative closure rule specification (models 2 and 4), likelihood ratio tests fail to reject the restriction that the coefficient on the $SIZE_{ijt}$ variable is equal to zero, although the restriction is rejected when comparing the absolute closure rule specifications (models 1 and 3).

The fifth and sixth columns add the other conditioning variables to the specification. Of the sectoral exposure measures, the *COMMERCIAL*_{ijt} and *REALESTATE*_{ijt} variables are robustly positive and significant, suggesting that exposure to these sectors increases the probability of bank closure. In contrast, the *AGRICULTURE*_{ijt} variable is insignificant. Of the remaining conditioning variables, the *CD*_{ijt} and *90DAYSLATE*_{ijt} variables both enter significantly with their predicted positive coefficients. The *NON-INTEREST*_{ijt} variable is insignificant.

Again, the base specification results are robust to the inclusion of these conditioning variables. Again, A_{ijt} and \overline{A}_{jt} enter significantly with quite similar coefficient estimates to those that they obtained in the base specifications. Both are again highly significant. Finally, the diagnostic and classification statistics strongly support the relative closure rule specification over a simple absolute closure rule. Likelihood ratio tests do reject the restrictions that the coefficients on the additional conditioning variables are jointly equal to zero, although there is again little improvement from the inclusion of the *SIZE_{ijt}* variable.

To investigate whether our results were driven by the large number of small banks in our sample, we reran the specification excluding banks that had less than \$50 million in book value of total assets during the sample period. This truncation reduced the number of both banking entities and bank failures in our specification roughly in half, from 12,303 to 6,052 and from 113 to 66, respectively. The results for this truncated sample are reported in Table 5.

The results are quite similar to those for the entire sample. The coefficient estimates are all highly significant and enter

TABLE 4 Logit Analysis Results: Entire Sample, 1992–1997 Dependent Variable: *FAIL*

Variables	Absolute closure rule (1)	Relative closure rule (2)	Absolute closure rule (3)	Relative closure rule (4)	Absolute closure rule (5)	Relative closure rule (6)
$\overline{A_{ijt}}$	-43.42** (3.04)	-71.81** (3.38)	-43.50** (3.03)	-73.10** (3.45)	-32.59** (3.50)	-69.74** (3.83)
\overline{A}_{jt}		55.24** (2.68)		56.38** (2.74)		52.26** (2.99)
SIZE			-2.19 E-7 (1.88 E-7)	-5.14 E-7* (2.40 E-7)	-2.32 E-7 (2.0 E-7)	-3.92 E-7 (2.43 E-7)
D92	41.76** (3.23)	10.89** (1.04)	41.90** (3.22)	11.10** (1.05)	28.02** (3.79)	10.07** (1.08)
D93	41.18** (3.27)	10.01** (1.06)	41.90** (3.22)	10.25** (1.07)	27.36** (3.82)	9.27** (1.09)
D94	40.26** (3.29)	9.29** (1.11)	40.40** (3.28)	9.53** (1.11)	26.44** (3.85)	8.51** (1.13)
D95	39.69** (3.33)	7.04** (1.12)	39.85** (3.32)	7.30** (1.13)	25.63** (3.88)	6.32** (1.14)
COMMERCIAL					6.71** (1.06)	5.30** (1.18)
AGRICULTURAL					-1.12 (2.14)	-0.28 (2.15)
REALESTATE					2.55** (0.78)	2.21** (0.78)
NON-INTEREST					1.16 (4.38)	0.36 (4.37)
CD					3.71** (1.49)	5.29** (1.57)
90DAYSLATE					35.91** (6.15)	26.66** (6.95)
Diagnostics	1 252 (2	051.00	1 050 40	0.42.04		
AIC Schwartz	1,253.63 1,298.89	951.28 1,005.60	1,252.43 1,306.75	943.04 1,006.41	1,152.86 1,261.50	886.31 1,004.00
 –2 log-likelihood # observations 	1,243.63	939.28 63 135	1,240.43	929.04 63,135	1,128.86 63,135	860.31 63,135
# observations Pseudo R^2 classification	63,135 .249	63,135 .433	63,135 .251	.439	.318	.480
Type I error	107/113	100/113	107/113	99/113	104/113	89/113
Type II error	0	6	0	8	6	13
Total correct	99.8%	99.8%	99.8%	99.8%	99.8%	99.8%

Note: See Table 1 for variable definitions. Standard errors are in parentheses. * and ** indicate Wald chi-squared statistical significance at 5-percent and 1-percent levels, respectively. Time dummies for years 1992 through 1995 were included in the specification. Dummy coefficient estimates are available upon request from authors. Type II error figure represents the number of non-events incorrectly designated as events.

with their predicted signs. \overline{A}_{jt} enters significantly positively with a coefficient of opposite sign and a similar magnitude as the absolute performance measure, A_{ijt} .¹⁸ Moreover, the

diagnostic statistics strongly suggest a role for relative performance in regulatory closure decisions, as specifications including relative measures continue to outperform those excluding relative performance. The inclusion of the relative performance measure strongly enhances sample fit and reduces Type I error.

^{18.} However, the two variables again fail to enter with equal and opposite coefficient estimates, which would satisfy a strong restriction implied by the formal model.

TABLE 5 Logit Analysis Results: Small Banks Excluded, 1992–1997 Dependent Variable: *FAIL*

Variables	Absolute closure rule (1)	Relative closure rule (2)	Absolute closure rule (3)	Relative closure rule (4)	Absolute closure rule (5)	Relative closure rule (6)
$\overline{A_{ijt}}$	-42.96** (4.27)	-73.25** (4.88)	-43.25** (4.26)	-74.18** (4.89)	-35.14** (4.81)	-71.76** (5.39)
\overline{A}_{jt}		53.44** (3.68)		54.26** (3.70)		50.95** (4.01)
SIZE			-2.75E-7 (2.16E-7)	-4.63E-7 (2.64E-7)	-2.68E-7 (2.17E-7)	-4.14E-7 (2.67E-7)
D92	41.36** (4.55)	14.90** (1.50)	41.78** (4.53)	15.18** (1.50)	31.24** (5.20)	14.47** (1.61)
D93	40.45** (4.61)	13.84** (1.53)	40.87** (4.59)	14.13** (1.54)	30.23** (5.25)	13.36** (1.64)
D94	40.25** (4.62)	13.89** (1.58)	40.67** (4.61)	14.15** (1.58)	30.06** (5.26)	13.36** (1.68)
D95	39.11** (4.68)	12.49** (1.69)	39.55** (4.66)	12.78** (1.69)	28.68** (5.34)	11.82** (1.80)
COMMERCIAL					5.56** (1.37)	4.87** (1.56)
AGRICULTURAL					-0.93 (4.01)	1.66 (3.87)
REALESTATE					1.31 (0.99)	1.26 (1.02)
NON-INTEREST					6.15 (5.32)	6.55 (5.63)
CD					4.22** (1.76)	4.78* (2.02)
90DAYSLATE					30.83** (8.93)	12.82 (10.06)
Diagnostics	200,12	501.04	70(10	576.00		
AIC Schwartz	728.17 769.90	581.94 632.02	726.18 776.25	576.29 634.72	695.30 795.45	564.79 673.30
-2 log-likelihood	718.17	632.02 569.94	714.18	634.72 562.29	671.30	673.30 538.79
# observations	31,143	31,143	31,143	31,143	31,143	31,143
Pseduo R^2 classification	.277	.426	.281	.434	.324	.458
Type I error	61/66	59/66	61/66	56/66	60/66	55/66
Type II error	0	3	0	9	2	3
Total correct	99.8%	99.8%	99.8%	99.8%	99.8%	99.8%

Notes: Analysis excludes banks with total assets below \$50 million at any time during the sample period. * and ** indicate Wald chi-squared statistical significance at 5-percent and 1-percent levels, respectively. Time dummies for years 1992 through 1995 were included in the specification. Dummy coefficient estimates are available upon request from authors. Type II error figure represents the number of non-events incorrectly designated as events.

Finally, the conditioning variables perform similarly to the results for the entire sample. There is again little evidence that bank size is a useful predictor of bank closure. Bank size fails to enter significantly, and both specifications appear to be insensitive to its inclusion. Among the other conditioning variables, the *COMMERCIAL*_{ijt} and *CD*_{ijt} variables are again robustly significant, while the *AGRICULTURE*_{ijt}, and *NON-INTEREST*_{ijt} variables again fail to enter significantly. The notable changes are in the *REALESTATE*_{ijt} and *90DAYSLATE*_{ijt} variables, which now fail to enter significantly under the relative closure rule specification (model 6). This discrepancy probably reflects some degree of collinearity between these variables, which provide information about loan quality and a bank's relative performance. Our empirical results give a strong indication that U.S. regulators considered relative performance in their closure decisions during the post-FDICIA period. This finding is consistent with the desirable policy in the theoretical model above.¹⁹ Moreover, the results are robust to the inclusion of the conditioning variables we consider, as well as the exclusion of small banks from the sample.

4. Conclusion

This paper examines the role of relative performance in bank closure decisions. We show that when banks are subject to common shocks, a closure rule that incorporates relative performance will be less costly than one based solely on absolute performance. Our empirical results provide robust evidence that relative performance has indeed been considered in bank closure decisions in the United States during the post-FDICIA period.

As we note earlier, neither the relative performance rule nor the absolute performance rule is time consistent in a static one-shot game. Instead, a regulator whose loss function solely involves minimizing expected taxpayer liability would always choose prompt closure when regulatory rules allow such behavior. As such, our empirical test should be viewed as a test of the joint hypothesis that the regulator would choose to pursue a relative closure policy and that he has the commitment capacity to do so. Our empirical results suggest that relative performance is incorporated in closure decisions and, therefore, that some form of commitment is achieved. The source of this commitment poses interesting questions beyond the scope of this paper. An interesting extension of this paper would be to endogenize the commitment power of the regulator as a function of its closure strategy. One might conjecture that this would strengthen the superiority of a relative closure rule, because the regulator could more easily commit to the pursuit of a less costly closure strategy.

Appendix

Proof of Proposition 1

Under the absolute closure rule in equation (4), ε^* satisfies

(13)
$$\varepsilon^* = m - \mu_i - \theta$$

and

(14)
$$\frac{\partial \varepsilon}{\partial \mu_i} = -1.$$

Substituting these into the bank's first-order condition, we obtain

(15)
$$(1+C_{\mu}) \bigg[1 - \int_{\underline{\theta}}^{\overline{\theta}} F(m-\mu_{i}-\theta) g(\theta) d\theta \bigg]$$
$$= V_{\mu} - (m+C) \mathbb{E} \big[f(\varepsilon^{*}) \big].$$

To ensure an interior solution for ε^* , we require the parameter restriction

(16)
$$\overline{\theta} + \max(\mu) + \underline{\varepsilon} < m < \underline{\theta} + \min(\mu) + \overline{\varepsilon}$$

which we adopt. Note that feasibility of this condition requires $\max(\mu) - \min(\mu) < \overline{\varepsilon} - \underline{\varepsilon}$.

Consider the special case $m = \overline{0}$, i.e., the closure rule is to close all banks on the loss of solvency. In this case, the bank's first-order condition becomes

(17)
$$\mu_{i}^{p} = V_{\mu}^{-1} \left\{ (1 + C_{\mu}) (1 - \mathbb{E} [F(-\mu_{i}^{p} - \theta)]) + C \mathbb{E} [f(-\mu_{i}^{p} - \theta)] \right\},$$

where μ_i^p is the privately optimal choice of effort.

As discussed in the text, we contrast the privately chosen level of effort with μ^s , the socially optimal effort level. The expected social stream of revenues includes expected bank revenues plus bank charter value, net of effort costs, plus expected regulatory liabilities under insolvency. The revenue stream therefore satisfies

(18)
$$\int_{\underline{\theta}}^{\overline{\theta}} \left[\int_{\underline{\varepsilon}}^{\overline{\varepsilon}} A_i f(\varepsilon) d\varepsilon + \int_{\varepsilon^*}^{\overline{\varepsilon}} Cf(\varepsilon) d\varepsilon \right] g(\theta) d\theta - V(\mu).$$

The first-order condition for μ^s then satisfies

(19)
$$\mu^{s} = V_{\mu}^{-1} \left\{ 1 + C \mathbb{E} [f(-\mu_{i}^{p} - \theta)] + C_{\mu} (1 - \mathbb{E} [F(-\mu_{i}^{p} - \theta)]) \right\}.$$

A comparison of equations (17) and (19) leads to Proposition 1. The proof follows directly from the fact that $V_{\mu\mu} > 0$, since $f(-\mu_i^p - \theta) < 1$ and $E[F(-\mu_i^p - \theta)] > 0$. As discussed in the text, this is the standard moral hazard result with limited liability: Since its losses are bounded from be-

^{19.} However, relative performance might also be important for considerations outside of our model, such as the ex post political-economy considerations discussed by Kane (1989).

low, the private bank chooses a lower level of effort because it does not share in the gains to returns in bankruptcy states. These are instead completely enjoyed by the regulator as a reduction in liabilities.

Also, note that when the level of effort is lower, the expected probability of bankruptcy, and hence the regulator's expected liability, will be higher.

Proof of Proposition 2

Under the relative closure rule in equation (7), ε^* satisfies

(20) $\varepsilon^* = n + \overline{\mu} - \mu_i$

and

(21)
$$\frac{\partial \varepsilon^*}{\partial \mu_i} = -1.$$

Substituting these into the first-order condition yields

(22)
$$\int_{n+\overline{\mu}-\mu_{i}}^{\overline{\varepsilon}} (1+C_{\mu})f(\varepsilon)d\varepsilon + [\overline{\mu}+\mathrm{E}(\theta)+n+C]\mathrm{E}[f(\varepsilon^{*})] = V_{\mu}.$$

In equilibrium, since banks are homogenous, all banks make the same effort decision and the first-order condition will satisfy

(23)
$$\int_{n}^{\varepsilon} (1+C_{\mu})f(\varepsilon)d\varepsilon + [\mu_{i}+\mathrm{E}(\theta)+n+C]\mathrm{E}[f(\varepsilon^{*})] = V_{\mu}.$$

As discussed in the text, we assume that ε_i is distributed uniformly on the interval $[\varepsilon, \overline{\varepsilon}]$ with density *f*.

Define $\widehat{\mu}$ as the level of effort which satisfies equation (15), i.e., the equilibrium level of effort implied by the absolute closure rule in equation (4). When ε_i is uniformly distributed, equation (15) can be simplified to yield the following relationship between *m* and $\widehat{\mu}$:

(24)
$$m = \frac{\left[V_{\widehat{\mu}} - Cf\right]\left(\overline{\varepsilon} - \underline{\varepsilon}\right) - \left[\overline{\varepsilon} + \widehat{\mu} + \mathrm{E}(\theta)\right]\left(1 + C_{\widehat{\mu}}\right)}{f\left(\overline{\varepsilon} - \underline{\varepsilon}\right) - \left(1 + C_{\widehat{\mu}}\right)}.$$

Next, substituting into the solution above for the level of effort under the relative closure rule, equation (23), the value of *n* which results in banks choosing effort level $\hat{\mu}$ satisfies

(25)
$$n = \frac{\left(\overline{\varepsilon} - \underline{\varepsilon}\right) \left[V_{\widehat{\mu}} - \left[\widehat{\mu} + \mathbf{E}(\theta) + C\right] f \right] - \overline{\varepsilon} \left(1 + C_{\widehat{\mu}}\right)}{f\left(\overline{\varepsilon} - \underline{\varepsilon}\right) - \left(1 + C_{\widehat{\mu}}\right)}.$$

Combining, m - n satisfies

(26)
$$m - n = \widehat{\mu} + \mathcal{E}(\theta).$$

Recall that A^m and A^n are the minimum realizations of A_i necessary to avoid closure under the absolute and relative closure rules. By equations (4) and (7), it is clear that

and

$$(28) A^n = n + \overline{A}.$$

Substituting from equations (26) and (5), and using the fact that in equilibrium $\overline{\mu} = \widehat{\mu}$,

(29)
$$A^n - A^m = \theta - \mathcal{E}(\theta),$$

which directly proves Proposition 2.

Proof of Proposition 3

Substituting into equations (7) and (9) for ε^* , and using the relationship between *m* and *n* and the fact that ε_i is uniformly distributed, L_m satisfies

(30)
$$L_m = -\int_{\underline{\theta}}^{\overline{\theta}} \int_{\underline{\varepsilon}}^{n-\theta+\mathrm{E}(\theta)} A_i(\widehat{\mu},\theta,\varepsilon_i) f(\varepsilon_i) d\varepsilon_i g(\theta) d\theta.$$

By equations (9) and (10),

(31)
$$L_m - L_n = \int_{\underline{\theta}}^{\overline{\theta}} \int_{n-\theta+E(\theta)}^n A_i(\widehat{\mu},\theta,\varepsilon_i) f(\varepsilon_i) d\varepsilon_i g(\theta) d\theta.$$

Assuming that ε_i is distributed uniformly, this simplifies to

(32)
$$L_m - L_n = \frac{1}{2} \left[\frac{Var(\theta)}{\overline{\varepsilon} - \underline{\varepsilon}} \right],$$

which gives us Proposition 3.

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