# Essays on the Taxation and Regulation of Financial Markets

by

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ABSTRACT

This thesis is a collection of three essays analyzing the economic effects of taxation, market structure, and the regulatory environment on financial markets, focusing in particular on financial intermediaries such as banks and mutual funds. The first chapter uses the unprecedented changes in the degree of competition in local banking markets that occurred between 1980 and 1994 to estimate the impact of market competition on the risk profile of commercial bank lending. There is evidence that increasing bank market power has been associated with reductions in the flow of bank capital to construction and land development loans, which are the highest-risk category of commercial bank loans. The magnitude of this effect is large: an increase in market concentration from the $25^{th}$ to the $75^{th}$ percentile is associated with a 20 percent drop in the share of bank lending going to construction loans. Robustness to a variety of control and instrumental variables strategies supports a causal interpretation of this empirical relationship.

The second chapter focuses again on the role of market structure in commercial banking markets, this time focusing on the relationship between market structure and consumer borrowing. This chapter uses data from the 1983 Survey of Consumer Finances to test empirically the relationship between banking market concentration and households' self-reported measures of credit rationing and constraint. There is strong evidence that more concentrated markets have fewer constrained borrowers, a result consistent with the Petersen-Rajan (1995) model of credit markets.

The third chapter, co-authored with Professor James Poterba, explores the relationship between the after-tax returns that taxable investors earn on equity mutual funds and the subsequent cash inflows to these funds. Previous studies have documented that funds with high pretax returns attract greater inflows. This chapter presents evidence, based on a large sample of retail equity mutual funds over the period 1993 to 1999, that after-tax returns have more explanatory power than pretax returns in explaining inflows. In addition, funds with large overhangs of unrealized capital gains experience smaller inflows, all else equal, than funds without such unrealized gains.

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## Contents

# Introduction

This thesis is a collection of three essays analyzing the economic effects of taxation, market structure, and the regulatory environment on financial markets, focusing in particular on financial intermediaries such as banks and mutual funds. The first chapter estimates the relationship between market concentration in commercial banking and the riskiness of bank loan portfolios. This chapter uses the unprecedented changes in the degree of competition in local banking markets that occurred between 1980 and 1994 to estimate the impact of market competition on the risk profile of commercial bank lending. There is evidence that increasing concentration has been associated with reductions in the flow of bank capital to construction and land development loans, which are the highest-risk category of commercial bank loans. The magnitude of this effect is large: an increase in concentration from the $25^{th}$ to the $75^{th}$ percentile is associated with a 20 percent drop in the share of bank lending going to construction loans. Robustness to a variety of control and instrumental variables strategies supports a causal interpretation of this empirical relationship. Increasing concentration also appears to increase average bank capitalization, raise the average share of assets loaned out to borrowers, and reduce bank failure rates during this period. Because the Federal Deposit Insurance Corporation stands ready to assume the assets and liabilities of failing banks, changes in bank portfolio risk affect the value of the government's contingent liability to the banking sector, as well as the health and stability of the financial sector and the larger economy.

The second chapter focuses again on the role of market structure in commercial banking markets, this time focusing on the relationship between market structure and consumer borrowing, a large and growing part of the American financial landscape. In 2000 the total amount of consumer borrowing amounted to over $1.5 trillion, or 15 percent of GDP. Consumer credit can help households improve the timing of consumption expenditures, often allowing them to purchase goods regardless of their level of financial assets currently available. Still, many households report being credit constrained, with requests for credit rejected or discouraged by potential lenders. Stiglitz and Weiss (1981) formalize models where credit rationing is an equilibrium feature, and Petersen and Rajan (1995) extend these types of models to banking markets of varying degrees of competition. This chapter uses data from the 1983 Survey of Consumer Finances to test empirically the relationship between banking market concentration and households' self-reported measures of credit rationing and constraint. There is strong evidence that more concentrated markets have fewer constrained borrowers, a result consistent with the Petersen-Rajan model of credit markets. Interest rates on consumer borrowing appear to decrease more sharply with age in competitive markets than in concentrated markets. This result is consistent with the cross-subsidization between new and existing borrowers that is central to the Petersen-Rajan model.

The third chapter, co-authored with Professor James Poterba, looks at investor reaction to the prospective tax burdens This final chapter explores the relationship between the after-tax returns that taxable investors earn on equity mutual funds and the subsequent cash inflows to these funds. Previous studies have documented that funds with high pretax returns attract greater inflows. This chapter presents evidence, based on a large sample of retail equity mutual funds over the period 1993 to 1999, that after-tax returns have more explanatory power than pretax returns in explaining inflows. In addition, funds with large overhangs of unrealized capital gains experience smaller inflows, all else equal, than funds without such unrealized gains. A large capital gain overhang discourages both gross fund inflows and gross outflows, but the inflow effect dominates the outflow effect.

*Chapter 1*
# Market structure and loan portfolios in commercial banking

## 1.1. Introduction

The period between 1980 and 1994 saw large changes in the degree of competition in local banking markets. These changes stemmed in part from more permissive government policy toward mergers and geographic expansion in the banking sector, increases in the rate at which new banks were chartered, and rising rates of bank failure. Across local banking markets, concentration moved in different directions; some metropolitan areas saw increasing banking sector concentration, while in other markets concentration fell. The relevance of observed market concentration as a measure of competition may also have fallen during this period, as almost all states enacted legislation that eased long-standing restrictions on the geographic expansion of banks and expanded the scope for potential competition to impact incumbent banks in local markets.

I use this recent historical record to estimate the relationship between market concentration and the risk profile of commercial bank lending. I find evidence that increasing competition, while reducing the overall share of assets that banks lend out, leads banks to shift lending toward the types of loans that have historically been most risky. This shift is associated with increasing overall portfolio risk and risk of bank failure. Because the federal government, through the Federal Deposit Insurance Corporation, stands ready to assume the assets and liabilities of failing banks, government policy that affects market concentration thus affects the value of the contingent liability from the government to the banking sector. Merton (1977), Kane (1985), and Boskin (1988) have pointed out that this contingent liability represents a very real and measurable cost borne by the federal government, though it is not explicitly accounted for in the official government budget

This paper is designed to evaluate two potential mechanisms through which concentration may affect bank risk and lending activity. The first mechanism, prominent in the FDIC's evaluation of the bank failures of the period, is that increasing competition erodes the value of existing banks and increases their willingness to invest in more speculative assets. However, if the return on safe assets is relatively unaffected by local market concentration, then competition may shift lending *away* from some risky loans. One mechanism for this effect, prominent in recent work by Petersen and Rajan (1995) is based on the implicit equity stake in "captive" borrowers that banks with market power enjoy. With risky new borrowers seeking loans, only banks with market power will have enough of an implicit equity stake in new borrowers to make risky loans profitable. The empirical evidence suggests that increasing concentration raises the total share of assets that banks lend out rather than invest in securities and other liquid assets, but shifts bank portfolios toward safer classes of loans, a result that is consistent with both types of models.

The paper proceeds in seven sections. The first section documents changing local banking market concentration, and describes the changing legislation regarding entry, both at the state and federal levels. The second section reviews the existing empirical literature on the impact of competition on bank risk-taking and on bank behavior more generally, while the third section addresses theoretical work on the risk-competition relationship. The fourth section describes aggregate banking portfolios and the characteristics of the sample that provides the backbone of my empirical analysis: 69,748 bank-year observations from FDIC Call Report data. The fifth section evaluates the empirical evidence from the 1980s and early 1990s, and finds that reductions in market concentration were associated with increasing investment in the riskiest class of loans and decreasing bank capitalization.

A sixth section discusses the implications of these empirical findings for the magnitude of the FDIC's implicit liability to the banking sector, finding evidence that changes in banking market concentration during the sample period affected the cost of the FDIC's guarantee to bank depositors. Bank regulatory policies that affected market concentration had an indirect but important impact on the cost of FDIC guarantee. This finding illustrates the principle that policies set by one government authority can often affect the cost of guarantees issued by another arm of government. A brief final section concludes.

### 1.2. Changing market concentration since 1980

The period since 1980 has seen enormous changes in the market structure of the American commercial banking industry. These changes reflect the confluence of several factors, including more permissive legislation for geographic expansion, a shift in the regulatory environment for new bank chartering, an increase in merger activity, and a wave of bank failures in the late 1980s and early 1990s. Measured at the national level, banking market concentration has increased dramatically over this period. At the level of local Metropolitan Statistical Areas (MSAs), the experience is much more varied: concentration has increased in about half of MSAs and decreased in the remaining half. Subsections that follow document first the observed changes to market structure over this period and then changes in banking policy behind them.

**1.2.1. Changing market concentration: empirical facts**

At the national level, a sequence of large bank mergers between 1980 and 1998 increased the share of assets held at the twenty-five largest banking organizations from 29.1 percent to 51.2 percent. Over the same period, the share of assets at the 100 largest banks increased from 46.8 percent to 62.6 percent (Rhoades, 2000). By 1998, more than one-third of the assets of the banking sector were held at the ten largest banks. Nationwide, the number of FDIC-insured commercial banking institutions fell from 14434 to 8581 between 1980 and 1998, a decline of over 40 percent.

This increasing concentration at the national level has attracted a great deal of attention and has often obscured the more varied experiences of individual local banking markets, where concentration, on average, has been almost constant. Data from Rhodes (2000) show that across urban areas, the average share of banking assets held by the largest three banks remained steady, rising from 66.4 percent to 66.6 percent, and the average Herfindahl-Hirschman Index (HHI) increased very slightly, rising from 1973 to 1976 index points.[1] Around the steady average, individual banking markets have varied substantially, with roughly half becoming more concentrated and half becoming less concentrated. Tables 1 and 2 present data based on the sample of 200 MSAs used in the analysis throughout this paper, and describe

[1] The Herfindahl-Hirschman Index is constructed from individual firms' market shares according to the following formula: HHI = 10000 * $\Sigma_i$ ($share_i^2$). A market with two equal-size firms, for example, would have an index value of 5000. The U.S. Justice Department uses a HHI of 1800 to divide moderately from highly concentrated markets.

the changing market concentration at the MSA level.[2] With 200 MSAs and 15 years of data over the period between 1980 and 1994, this sample has 3000 MSA-year observations.[3] The characteristics of this sample differ slightly from the numbers reported by the Federal Reserve study above, but the broad outlines of the data are the same. Table 1 shows that in my sample, with metropolitan areas weighted equally, the median Herfindahl Index was 1782.9. Half of the MSA-year observations are within the 1353-2323 interquartile range. The median Herfindahl Index in 1980 was 1736, 25 percent of the observations had scores less than 1273 and 25 percent had scores greater than 2400. The median in 1994 was 1784, an increase of 48 index points from 14 years earlier. While the mean and median have changed little over the period, the variation across MSAs has decreased substantially. The standard deviation fell by 17.4 percent, from 807 in 1980 to 667 in 1994, and the interquartile range also narrowed considerably.

The steady mean concentration in this sample of MSAs conceals a great deal of variation across the individual markets, with some markets becoming substantially more concentrated and some becoming substantially less concentrated. Table 2 shows the variation in the experiences of different metropolitan areas. On an unweighted basis, the mean change in concentration over the 14 years is 40.8 Herfindahl Index points. But 25 percent of MSAs saw decreases in concentration of greater than 258 Herfindahl Index points, and 25 percent saw increases in concentration of more than 387 points. The rising concentration measured at the national level, coupled with the varied experiences of local markets, reflects the fact that over this period, a declining number of increasingly regional and national banks were competing over multi-MSA market areas.

### 1.2.2. Banking policy changes

Much of the change documented above stemmed from changes in government regulation of the banking sector. Several regulators direct policy in this sector is directed, including the Federal Reserve Board (Fed), the Office of Comptroller of Currency (OCC), the Federal Deposit Insurance Corporation

[2] I am grateful to Philip Strahan for providing these data, which are also the basis for the analysis of section 5.
[3] These MSAs are chosen for relatively consistent definitions over time and exclude MSAs that are merged into other MSAs during the sample period.

(FDIC), and the elements of the Federal Trade Commission and Justice Department's Antitrust Division that focus on the banking system. Beginning with regulation of merger activity, each of these regulators during the 1980s was much more permissive than in previous decades. Mergers in the banking sector can be divided into two types, depending on whether the merging banks are located in the same market: "market-extension" mergers take place between banks in different locations, and lead to a combined bank that has extended geographic reach but does not necessarily have greater market power in its regions;[4] "horizontal" mergers occur between banks operating in the same location, and generally increase measured local market concentration. Increasing permissiveness applied to both horizontal and to market-extension mergers, with changing attitudes at antitrust authorities initiating the horizontal merger boom and changes in branching legislation prompting an increase in market-extension mergers.

Focusing on regulation of "horizontal" mergers prior to 1980, the Fed had very broad powers to block proposed mergers on the basis of "potential anticompetitive effects", even if the Fed could not demonstrate that the proposed merger would increase measured market concentration. The U.S. Supreme Court's 1963 ruling that obligated the Justice Department to prevent mergers that were likely to significantly increase local banking markets' concentration provided another basis for banking antitrust policy.[5] The Bank Merger Act Amendments of 1966 gave the Justice Department authority to stay any merger that violated this standard, putting enormous enforcement power behind the legal authority granted in 1963. Because most significant mergers were likely to increase observed market concentration, and because the Justice Department could automatically prevent any merger that violated this standard, merger activity prior to 1980 remained at low levels.

At the beginning of the 1980s, this regulatory authority to prevent bank mergers was sharply curtailed. A U.S. Appeals Court decision in 1981 restricted the Federal Reserve's ability to prevent

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[4] Market-extending mergers may increase concentration measures based on geographic areas wider than the MSA. While it is generally accepted that the metropolitan area is the relevant market scale for commercial bank competition, if banks that compete in many markets behave differently from banks that compete only in one market, market-extension mergers may raise effective concentration without raising MSA-level concentration measures. For more on the multi-market contact literature in banking, see Heggestad and Rhoades (1983).

[5] United States v. Philadelphia National Bank, 374 U.S. 321 (1963). Among other things, the Court ruled here that antitrust legislation applied to banking, a matter that had previously been in doubt.

proposed mergers, ruling that the Fed needed more concrete reasons than nebulous "potential effects" to block proposed mergers. Following this decision, the Federal Reserve became substantially less aggressive about blocking proposed mergers. The Reagan Administration Justice Department and FTC appointments ushered in an era of more relaxed merger regulation. Indeed, the head of the Reagan transition team at the FTC proposed eliminating the Commission's entire antitrust arm. As Assistant Attorney General William Baxter noted, "[The Reagan Administration's] underlying philosophy is that mergers are a very, very healthy phenomena of the capital market and should not be interfered with except under exceptional circumstances." The 1982 and 1984 Horizontal Merger Guidelines set forth the analytical framework behind this relaxed enforcement attitude.

As regulatory policy toward horizontal mergers was becoming more relaxed, legislative restrictions preventing market-extension mergers were also beginning to fall. At the end of the 1970s, most states still limited the geographic expansion of banks; often, these state laws prevented both mergers between banks in different markets and de novo bank branching into new markets. These limitations reflected, in part, America's historical wariness of concentrations of financial power, and they created a banking sector that was fragmented and vulnerable to sectoral and regional shocks (Calomiris, 1993).

Until the 1990s, the Douglas Amendment to the 1956 Bank Holding Company Act was the key restriction on interstate branching. This amendment prohibited a bank holding company (BHC) from acquiring a target bank in another state unless the target state permitted the acquisition. No state did so until 1978, when Maine first permitted out-of-state banks to purchase banks within its borders. Over the following decade, most states entered into reciprocal agreements enabling banks from neighboring states to branch within each others' borders. By 1990, all states but Hawaii allowed at least some out-of-state banks to branch within their borders. This sequence of changes culminated in the passage in 1994 of the Riegle-Neal Interstate Banking and Branching Efficiency Act, which effectively allowed nationwide interstate branch banking.

States simultaneously relaxed restrictions on within-state branching. In 1975, most states restricted in some way banks' ability to open new branches, and only fourteen states permitted full statewide branching. Sometimes branching was allowed only by the purchase of existing branches ("branching by merger"); in other states, banks were allowed to start up entirely new branches ("de novo branching"). Often states passed legislation at the same time allowing both types. By 1992, all but three states (Arkansas, Iowa, and Mississippi) allowed full statewide branch banking. The upswing in market-extension mergers, from 105 in 1980 to a peak of 436 in 1987, reflects the increasingly permissive environment for bank expansion.

In theory, the relaxation of long-standing branching restrictions may have ambiguous effects on the observed competitiveness of banking markets. Allowing de novo branching allows new competitors to enter previously closed local markets by opening new branches, while allowing branching by merger can allow increases in concentration, as banks expand into new markets by purchasing existing branches. Regardless of the effect on observed concentration, however, the relaxation of restrictions introduced potential competition in markets, even markets that appeared fairly concentrated. For this reason, the empirical work in section five generally estimates the impact of concentration separately in the years before and after deregulation of branching restrictions.

New bank chartering and rose in the 1980s and 1990s as well. Like the increases in merger and branching activity, the growth of new bank chartering stemmed from changing regulatory attitudes. In the early 1980s, Congress directed to the OCC (the regulator responsible for new bank chartering) to immediately increase the pace at which it chartered new banks. The OCC responded by becoming substantially more lenient in granting charter applications, and the percentage of applications for charters approved by the OCC rose from 58% in the 1970s to 89% during the 1980s. Many state chartering authorities followed suit and increased their own chartering of new banks. At the peak of the mid-1980s chartering boom, newly chartered banks as a share of all banks topped 3 percent, where it had been around 1 percent only a few years before.

The period that followed the mid-1980s chartering boom saw the most spectacular spate of bank failures since the early 1930s. Banks failed at rates unprecedented in the postwar period; in both 1989 and 1990 more than 1.5 percent of existing banks failed. This increase in failures reflected fallout from energy and real estate crises in Texas and the Southwest, as well as prolonged recessions in California and in the Northeast.

### 1.3. Banking market concentration: existing empirical literature

The roots of the literature on market concentration and risk go back at least to the first half of the 20th century; John Hicks' famous remark that "the best of all monopoly profits is the quiet life" is famous even to non-economists. His intuition that firms will not only use market power to raise expected profits, but also seek to lower the variability of their profits, has a powerful appeal. Caves (1970) touched on the same notion, noting that "...a significant portion of the potential profits latent in [the large firm's] monopoly position is taken in the form of avoiding uncertainty, with important allocative effects on the economy." This Hicks-Galbraith-Caves hypothesis inspired empirical work on the banking sector by Edwards and Heggestad (1973) and Rhoades and Rutz (1982). Edwards and Heggestad, looking at 66 large banks over the 1954-1966 period, find that the variance-mean ratio of profits[6] is decreasing in (cross-sectional) market concentration. Rhoades and Rutz, looking at 6,500 unit banks over the 1969-1978 period, also find that banks in more concentrated markets have less variable net income and report higher capitalization and profits. Taken together, these papers document a robust cross-sectional relationship over twenty-five years between banking market concentration and profit variability and were interpreted as providing empirical support for the Hicks-Galbraith-Caves hypothesis.

The FDIC and FSLIC crises of the 1980s motivated a later literature on the relationship between deposit insurance and risk. Keeley (1990) empirically addresses the same question as Edwards and Heggestad and Rhoades and Rutz. Analyzing a sample of the 150 largest bank holding companies, he finds evidence that the relaxation of state branching restrictions reduces the market-to-book ratios and equity ratios of incumbent commercial banks. These banks, newly exposed to potential competition, also pay higher interest rates on uninsured CDs. He concludes that banks with reduced market power have

[6] The variance-mean ratio of profits is the measured variance of a bank's earnings divided by their mean.

increased portfolio risk, and pay higher default premia on these uninsured deposits.[7] In looking at the impact of deregulation, Keeley's paper is similar to more recent work by Jayaratne and Strahan (1998, 1999). They analyze the impact of the relaxation of geographic restrictions on bank performance, and present evidence that branching restrictions slow the process of natural selection by which inefficient banks lose market share to their more efficient competitors. Jayaratne and Strahan find that deregulation is followed by increases in efficiency, as well as reductions in costs and loan losses. The finding that reductions in loan losses follow the easing of restrictions seems to contrast with Keeley's assertion that deregulation led to increases in risk, but their larger sample and inclusion of more recent data may explain this difference.

While most of the papers cited above concern the concentration-risk relationship, Gilbert (1984) surveys a voluminous empirical literature on the relationship between market concentration, interest rates, and bank profits. The basic conclusion of his survey is that increases in competition lead to rising deposit interest rates, falling lending interest rates, and reduced bank profitability. Reflecting enormous variation in sample and empirical technique, point estimates of the relationships listed above vary substantially. In particular, estimates of the impact of a 10 percentage point increase in (3-firm) market concentration on net income as a share of assets range from 1.7 to 8.6 basis points.[8]

More recent work by Berger and Hannan (1998) extends the literature Gilbert reviews by evaluating the welfare costs of market power in commercial banking. They show that because market power allows inefficient banks to survive, the costs of monopoly are much greater than measured by simple reductions in output and higher markups. In a sample of 5000 banks, they find that banks in more concentrated markets have less operating efficiency; Berger and Hannan derive high estimates of the welfare cost of market power. While their paper does not focus on risk-taking, its focus on the welfare cost of monopoly is an important counterpoint to the analysis that follows. Finally, work by Sapienza (2002) uses a unique dataset that identifies the contract terms of loans to individual borrowers for a

[7] Keeley argues that the interest rates for large uninsured CDs are determined at the national level, so that local market competition exerts no effect on these rates independent of the effect of competition on risk.
[8] See Demsetz (1973) and Baumol (1982) for criticism of the structure-conduct-performance literature.

sample of Italian banks. With these data she addresses the empirical debate regarding the impact of bank mergers on the supply of loans to small businesses. She finds that when the acquired bank is large, mergers reduce the supply of loans to small borrowers. When the acquired bank has a low market share, however, mergers do not reduce loans to small businesses.

This paper offers several innovations to the literature on market concentration and risk. First, I follow the recent literature on market structure and small business lending by looking at banks' actual portfolio holdings of banks and documenting the shifts in portfolio allocation that accompany market structure changes. Second, I examine at the structure-conduct-performance relationship both before and after deregulation. In the period prior to deregulation, when potential competition is precluded, observed market concentration is a true proxy for market power. After deregulation the relationship between concentration and market power is more ambiguous due to the existence of potential competition. Finally, this paper considers the impacts of both concentration and of deregulation on portfolio holdings and risk, and employs a large dataset: all metropolitan commercial banks between 1980 and 1994.

### 1.4. Banking market concentration: theory

Beginning with the seminal work of Merton (1977), economists have understood that deposit insurance introduces moral hazard and may induce banks to increase portfolio risk. Keeley (1990) and Hellman, Murdock, and Stiglitz (2000) touch on this notion as well. Because depositors are insured by the FDIC, they will place deposits with the bank offering the highest interest rates, regardless of the risk of the bank's underlying assets. Because bank owners enjoy limited liability, they have a call option on the value of their loan portfolio, with a strike price equal to the cost of their deposits. As in other options models, the bank has an incentive to increase portfolio risk, which effects a transfer from the FDIC to the bank. Addressing this moral hazard problem is a key component of bank regulation.

Figure 1 more concretely illustrates this intuition. A bank pays deposit interest rate D, and has the opportunity to invest in one of three assets. Each of the assets has the same expected return. There is a safe asset, which pays S with certainty, a risky asset, which pays $S + K_S$ with probability ½ and $S - K_S$ with probability ½, and an extremely risky asset, which pays $S + K_L$ with probability ½ and $S - K_L$ ($K_L >$

$K_S$) with probability ½. As the figure shows, very small additions of risk to the safe asset's return do not increase the bank's expected return; because the bank will remain in operation regardless of which state is realized, the pain of the bad state balances the profits of the good state. Beyond a certain point, however, increases in risk increase the bank's expected profit because the limited liability constraint places an upper bound on the "pain" of the bad-state outcome. Because of this nonlinearity in the bank's return to its portfolio, the expected one-period profit to the bank increases in the scale of risk that the bank takes on.

Equations (1) and (2) describe the value of banks investing this period in safe and very risky assets, and thereafter investing in only the safe asset ($V_S$ and $V_R$, respectively).

(1) $$V_S = (S - D) + (S - D) * [\beta/(1 - \beta)]$$

(2) $$V_R = ½ * (S + K - D) + (S - D) * ½ * [\beta/(1 - \beta)]$$

The discount rate is $\beta$, meaning that profits of X one period hence are valued at $\beta X$ today, and a perpetuity of X starting today is valued at $X/(1-\beta)$. The first part of each expression gives the one-period expected profit from the strategy, and the second part gives the discounted flow of expected profits from investing in the safe asset.

K represents the size of the gamble available to a bank choosing the risky strategy. Because the bank enjoys both the entire upside of a successful gamble and the ability to put its assets and liabilities onto the FDIC in the event of bankruptcy, the private value of the risky bank ($V_R$) is everywhere increasing in K. The increase in $V_R$ from the mean-preserving increase in the variance of the risky asset is mirrored by a reduction in the value of the FDIC, which must take on the bank's assets and liabilities in the event of default.

Define a level of K, as a function of the other parameters, such that the monopolist is indifferent between safe and risky assets. This value K* represents the minimal attractiveness of the risky asset necessary to induce a bank to gamble. If we think of banks occasionally observing draws of K from some distribution, then a reduction in K* means that banks opt to gamble more frequently than before. Equation (3) below shows that this level of K is decreasing in the competitiveness of the marketplace:

(3) $V_S(K^*) = V_R(K^*)$

Equation (3) above represents the solution when equations (1) and (2) above are set equal to each other. This solution defines implicitly a level K* as a function of the other parameters of the model:

(3') $K^* = (S - D) / (1 - \beta)$

This level K* is decreasing in the deposit interest rate D, which is the proxy for the level of competitiveness in the bank's market.

(3'') $dK^*/dD = -1 / (1 - \beta) < 0$

From equations (1) and (2), increasing competition, proxied by increases in D, reduces $V_S$ by more than $V_R$; increases in competition reduce the value of the safe bank more than the risky bank. This difference is the basis for the intuition that monopolist banks will invest in safe assets; the risk of losing monopoly profits can be a deterrent to risky behavior. Increasing competition, by reducing the future profit streams of safely-managed banks, erodes incentives to invest in safe assets. Thus increasing competition, by this reasoning, may shift bank portfolios towards riskier types of loans.

In a more complete model, competition among banks affects interest rates on bank loans as well as deposits. A recent line of research by Petersen and Rajan (1995; see also papers by Dinc(2000), Hauswald and Marquez (2000), and Marquez (2000)) explores the impact of credit market competition on relationship lending. In the Petersen-Rajan, model loans to credit-constrained firms generate subsequent rents at the surviving firms, which a bank in a monopolistic lending market can extract through interest rates on subsequent loans to the survivors. Because competition among banks reduces their ability to extract these ex-post rents from the firm, as markets become less concentrated banks can only profitably lend to the most creditworthy firms. Only banks with monopoly power will be able to extract, ex-post, the rent necessary to make investment in risky firms profitable. It is important to note that deposit insurance and bank failure do not enter the Petersen-Rajan model. The cost of lending to credit-constrained firms, which in this model comes from their probability of failure, could just as easily be thought of as the bank's cost of gathering information about new borrowers. The crux of this model is that ex-post competition can reduce banks' incentives to invest in relationships with potential borrowers, and shift bank portfolios towards assets (such as securities) where these banker-borrower relationships are less important.

Figure 2 illustrates a very simple formulation of Petersen-Rajan effects. In period 0, the firm makes a loan to a credit-constrained firm. This firm will survive with probability p, and p denotes the 'riskiness' of the loan. This firm, should it survive, will repay the loan with interest in period 1. At that time, it takes out another loan with that bank. When the second loan is taken out, the bank's market power M determines how much rent the bank can extract.

If the bank's per-period gross cost of capital is (1+r), that bank's total profit from a loan of riskiness p is:

(4) $\Pi^{risky} = [((p * R * L_1) / (1+r)) - L_1] + p * [((M * L_2) / (1+r)^2) - (L_2 / (1+r))]$

and the boundary condition separating profitable and unprofitable risky loans is:

(5) $\Pi^{risky}(M,p) = 0$

Equation (5) implicitly defines a value M*(p), a function of p, above which a given loan is profitable:

(6) $M^*(p) = (1+r) * [1 + (L_1 / L_2) * [((1+r) / p) - R]]$

The equation above defines a level of market power M*(p) such that for any given level of p, the risky loan is profitable for the firm. Differentiating that condition gives the following expression:

(7) $dM^*(p)/dp = -(L_1 / L_2)*((1+r)/p)^2 < 0$

From equation (7) comes the intuition that the market power necessary to make a risky loan profitable increases in the risk of that loan. The Petersen-Rajan model provides an intuition for why the effective return to risky loans may fall relative to more liquid assets as local markets become less concentrated.

The models described above provide a guide for interpreting the empirical evidence of the following sections, which represent an attempt to sort out the empirical importance of moral hazard and

Petersen-Rajan-style effects on commercial bank portfolios. In line with the moral hazard model above, evidence that risky asset holdings increase with competition would be evidence of moral hazard effects, while evidence that banks in competitive environments shift away from relationship-intensive types of lending towards more liquid assets would be consistent with the Petersen-Rajan model.

### 1.5. Empirical approach

Empirical analysis of the competition-portfolio risk relationship motivated by the previous sections is difficult because the risk of a bank portfolio is hard to observe, whether ex-ante or ex-post. Loans that are ex-ante relatively safe occasionally fail, and relatively risky loans are frequently paid off. My approach is to analyze portfolio allocation across sectors, and in particular on the share of loans going to sectors that are typically the riskiest. I also focus directly on bank capitalization and failure rates.

A dataset drawn from the FDIC Reports of Condition and Income (Call Reports) over the period between 1980 and 1994 forms the backbone of the empirical analysis.[9] All banks regulated by the Federal Reserve, FDIC, or OCC are required to submit quarterly reports detailing their assets, liabilities, and income. This paper uses the fourth quarter reports over a 15-year period; excluding observations outside of MSAs and observations that are missing data leaves a sample of 69,748 commercial bank-year observations.[10]

I link the FDIC Call Report data to two auxiliary datasets. The first provides annual Herfindahl Index numbers for almost all MSAs, and the second gives the dates at which each state relaxed restrictions on bank branching activity. The aggregate Herfindahl Index numbers are constructed from underlying branch and office level data from the FDIC's Summary of Deposits database. These data have also been used in a recent series of papers by Jayaratne and Strahan (1998, 1999). Where MSAs stretch across state boundaries, I assign that MSA to the state with the bulk of the population.

[9] I am very grateful to Adam Ashcraft for providing SAS programs used to manipulate these data.
[10] Census MSA definitions occasionally change, with previously separate MSAs merging and other MSAs being split. I exclude observations from MSAs that merged with other MSAs during the sample period and observations from MSAs that do not exist as separate entities throughout the sample period.

Table 4 describes portfolio holdings in my sample of 69,748 bank-year observations. At the aggregate level, over 86% of bank assets are interest-earning. The bulk are loans and leases, and securities comprise most of the remainder of assets. The largest loan classes are commercial loans, consumer loans, and real estate loans. Loans to these different sectors have different risk characteristics; traditionally, lending for construction and land development projects has been among the riskier activities of commercial banks. Construction loans between 1980 and 1994 were risky foremost because they were generally not secured by existing assets, unlike home and nonresidential mortgages, which are secured by existing property. Other reasons for the high risk of construction loans include lags between lending and project completion that expose banks to interim market fluctuations and the strong systematic component of the riskiness of individual construction loans. Below I present more detailed evidence about the contribution of construction loans to bank portfolio risk.

The first three lines of Table 4 show the range of bank size, in current-dollar amounts. The mean bank-year observation in the sample has $367.6 million in assets, $226.6 million of which are invested bank loan portfolios. On the liability side, the mean bank-year observation has deposits amounting to $283.8 million. The medians are substantially lower, reflecting the skewed nature of the distribution of bank sizes.

The average bank in the sample lends out 56.1 percent of its assets, and the interquartile range runs from 47.5 percent to 65.9 percent. In the individual years that make up the sample, the average ranges from just below 54 percent early on to above 58 percent through the middle and late 1980s and again in 1994. Over 80 percent of bank-year observations have positive amounts of loans to construction projects; for the mean bank these loans amount to 4.7 percent of the total portfolio of assets. There is a tail of bank-year observations for which these types of loans are very important: for the 90$^{th}$ percentile bank, these types of loans amount to 12.3 percent of the loan portfolio. Among the other types of loans, commercial loans, home mortgage loans, and consumer loans all make up between 13 and 14 percent of assets at the mean bank; nonresidential loans account for somewhat less.

Table 5 shows the share of banks that failed over the period. The sample in 1980 contains 5147 banks, of which 0.08 percent fail in the next year and 0.25 percent in the next two years. Of these banks, 8.22 percent eventually fail, and these failing banks manage 6.16 percent of the assets in the sample that year. Table 5 shows the growth in bank failures during the period; 2.64 percent of the 4583 banks in the sample in 1988 fail within the next year.

Table 6 presents the first evidence in this paper on the relationship between exposure to the commercial real estate sector and bank failure. The first three rows of the table show capitalization levels of all banks, banks that eventually fail, and banks that do not fail, in 1980, 1985, and 1990. In 1980 and 1985, both banks that fail and those that survive report approximately the same capitalization, although by 1990, the banks that will eventually fail are reporting substantially lower capitalizations than the surviving banks. Table 6 shows that throughout the period banks that eventually fail have on average twice the exposure to construction loans of the banks that will survive.

Table 7 moves further to motivate differences in bank portfolio weights as a signal for risky behavior. In each year between 1980 and 1994 I run a linear probability model, equation (8):

$$\text{(8)} \qquad \mathrm{I}(\textit{ever fail})_{i,t}^{MSA} = \alpha + \Sigma\, \beta_1 * \mathrm{SHR}_{j,i,t}^{MSA} + \varepsilon_{i,t}$$

The dummy dependent variable in this model is one if the bank fails between that year and 1998 and zero otherwise. The independent variables $\mathrm{SHR}_{j,i,t}^{MSA}$ are the shares of bank i's assets at time t devoted to asset class j. Asset classes include construction and land development loans, nonresidential mortgages, residential mortgages, commercial and industrial loans, loans to individuals, and liquid assets. For each year, Table 7 reports the coefficients on the share variables from equation (8), as well as the number of banks in each year's regression and the share of those banks that eventually fail. In addition to the rows showing separate regressions for each year, the top row of Table 7 presents results from a regression that pools each of the years into a common sample and estimates a version of equation (8) that includes year dummy variables as well as portfolio share variables.

The results in Table 7 are large in economic magnitude, and reflect the outsize risk associated with construction lending. Increasing construction lending by one percentage point in 1983 is associated with a 1.28 percentage point increase in a bank's probability of eventual failure. Comparable figures for commercial and home mortgage lending are 0.45 and –0.08 percentage points, respectively. The decline in the reported magnitudes of all coefficients between 1980 and 1994 reflects the declining share of banks that eventually fail. But in each year until 1994, the coefficient on construction lending is higher, usually significantly higher, than the coefficients on any of the competing loan classes. Consistent with the popular wisdom, construction lending appears to be a risky sector for bank lending. This empirical regularity motivates the use of construction lending as a proxy for risky behavior in section 5.

### 1.6. Results

Motivated by the theoretical analysis of section 3, and using the FDIC Call Report dataset described in section 4, I turn in this section to empirical analysis of the relationship between banking market concentration and characteristics of bank portfolios. The section begins with reduced-form analysis of market concentration and portfolio characteristics and continues through a variety of control and instrumental variables strategies designed to assess whether the relationship between market power and risky lending is causal or merely reflects spurious correlation. The evidence, on the whole, supports the hypothesis that changes in market concentration during the sample period caused changes in lending to risky sectors.

#### 1.6.1. Concentration and portfolio shares

The first regressions are reduced form, and fit bank portfolio shares on MSA Herfindahl Indexes as in equation (9):

$$(9) \qquad SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}$$

where $SHR_{j,i,t}^{MSA}$ is the share of bank i's portfolio that at time t is devoted to asset class j. $HHI_t^{MSA}$ is the Herfindahl-Hirschmann Index, which measures the concentration of the MSA banking sector at time t. $X_{i,t}^{MSA}$, a vector of control variables, includes individual bank size, the size of the MSA banking market (proxied by MSA bank deposits), and county-level employment growth and employment concentration measures.[11] The vector of controls also at times includes year, MSA, and region-year dummies, state-by-state fixed effects and trends, and MSA-specific linear trends. Table 8 shows empirical results based on equation (9). In Table 8 each row presents results for a different portfolio share variable, and reading along the row gives the coefficients on market concentration for a different set of controls and fixed effects.

The variety of fixed-effect strategies illustrates the cross-sectional and time series relationships between concentration and portfolio allocation. Column (1) has neither control variables nor fixed effects of any kind. Column (2) has control variables for bank size, but no fixed effects. Column (3) adds year fixed effects, and column (4) adds region-by-year fixed effects, controlling for the different patterns over time across the 9 census-defined regions in the US. Column (5) has only MSA fixed effects, and column (6) adds both MSA and year fixed effects. Column (7) includes all of the controls of column (6), as well as MSA-specific linear trends. Columns (6) and (7), which control for both fixed variation across MSAs, and for variation across time in overall lending patterns, are the preferred regressions.

The most robust of the results in Table 8 is that increasing concentration of the banking sector reduces the share of bank assets loaned to construction projects. Loans to these projects are the riskiest of the loan categories for which data exist. Also robust is the relationship between concentration and bank capitalization. A 500-point increase in the MSA Herfindahl Index is associated with a 35 to 40 basis point increase in the ratio of equity to assets. The finding that increasing concentration increases the total share of assets loaned out, as opposed to invested in liquid securities and cash, is somewhat less robust. While columns (1) through (6) support the notion that increasing concentration and increased total lending are linked, column (7) reveals that this relationship is not robust to the inclusion of MSA-specific trend variables. This difference may reflect the different time horizon of effects picked up by the regressions reported in columns (6) and (7). Column (6), without MSA trends, picks up long-horizon

[11] The employment growth measure is a predicted employment growth measure, constructed by multiplying lagged county employment shares by national growth rates for different 2-digit SIC codes. The employment concentration measure is the county-level Herfindahl Index of employment shares at the 2-digit SIC level.

empirical correlation between concentration and portfolio shares, while column (7), with trends removed, picks up shorter-horizon shifts than column (6).

Again, the coefficients of Table 8 are large in economic magnitude. Focusing on the point estimate from column (6), an increase in market concentration of 500 Herfindahl Index points is associated with a 33 basis-point reduction in construction loans as a share of assets, and a 52 basis-point reduction in construction lending as a share of loans. With total construction lending in 1990 accounting for 3.97 percent of $3.4 trillion in commercial bank assets, a 33-basis point reduction would amount to an $11 billion reduction in construction loans outstanding, or over 10 percent of the $108 billion in private nonresidental construction spending reported by the Census Bureau in that year.

Viewed in the context of section 3, the results above provide strong evidence for the moral hazard effect of market concentration. Columns (1) through (6) also suggest of Petersen-Rajan effects, with increasing concentration raising the total share of assets that banks loan out. Again, however, adding MSA-specific trends drastically changes the estimated coefficients in the regressions of total lending. The evidence consistent with the moral hazard model is much more robust to the inclusion of MSA-specific trends.

**1.6.2. Concentration and portfolio shares among different types of banks**

In this section I evaluate the relationship between concentration and the share of loans going to the riskiest category across different types of banks. These results help assess whether the strong reduced-form relationship between market power and construction lending reflects a true causal relationship or spurious statistical correlation.

Columns (1) and (2) of Table 9 reflect concern about possible reverse causation or spurious correlation by highlighting a sample of banks whose activities had relatively limited effects on changes in market concentration in their local areas. These columns are based on a sample of banks that are never involved in mergers, and whose size ranks them in the bottom 95 percent of banks in the sample. While these banks' activities have less effect on observed market concentration than larger or actively merging banks, the moral hazard model of section 3 suggests that changes in concentration will affect their behavior. The results in columns (1) and (2) of Table 9 are consistent with those in Table 8 and help support a causal interpretation of the relationship between concentration and risk. Among this sample of smaller and non-merging banks, a 500 point Herfindahl Index increase is associated with a 60 to 65 basis point change in construction lending as a share of total loans.

Columns (3) through (6) evaluate the relationship between concentration and portfolio shares across different levels of bank capitalization. In the analysis of the third section, the total capital that banks place at risk consists of both explicit bank capital, measured as the share of equity in assets, and implicit capital based on the opportunity to earn profits from market power in the future. Equivalent changes in the level of this implicit capital, stemming from changes in market concentration, represent a larger percentage change in the total capital of banks with lower amounts of explicit capital. While one would not a priori expect a spurious correlation between construction lending and market structure to affect better (explicit) capitalized banks differently from their undercapitalized competitors, columns (3) through (6) suggest that construction lending by banks with lower levels of explicit capital is more sensitive to market power than for banks with higher levels of explicit capital. Dividing the sample at 8 percent capitalization, for banks in the lower-capitalization group, the coefficient point estimate is –1.20 (standard error 0.19), while for the more highly capitalized banks the coefficient estimate is –0.74 (0.20). This difference again supports a causal interpretation of the relationship between market concentration and the share of lending going to highly risky sectors.

Table 10 focuses on the relationship between concentration and portfolio shares across different types of MSAs. Columns (1) through (4) split the sample into MSAs that see concentration increases over the period and MSAs that see decreases. For construction lending, the evidence is fairly consistent: both types of MSAs see a negative relationship between concentration and the share of lending going to this risky category. The same is true for bank equity ratios; in both samples the relationship between concentration and capitalization is robust. Again, the results are more mixed for total lending. The relationship between concentration and total lending appears positive among the sample of MSAs with increasing concentration, consistent with the Petersen-Rajan model. For MSAs with decreasing concentration, however, there appears to be a negative relationship between concentration and total lending.

Columns (5) through (8) of Table 10 focus on the concentration-portfolio share relationships across different levels of market concentration. The results here are mixed, especially for construction lending. The relationship between concentration and construction lending is negative for the 50479 MSA-year observations corresponding to Herfindahl Indexes in excess of 1000. A Herfindahl Index of 1000 corresponds to a hypothetical market with 10 equal-size banks, and Herfindahl Indexes below 1000 correspond to highly competitive commercial banking markets. Among these most concentrated markets, there appears to be a *positive* relationship between concentration and construction lending. In these highly competitive markets, there is no evidence that small reductions in concentration are associated with increases in construction lending. If anything, the relationship in this small sample appears to go in the other direction.

Columns (1) and (2) of Table 11 focus on a sample of 34360 bank-year observations drawn from MSA-years in which no banks have yet failed. For each MSA, all banks are included until the year in which the first bank fails, after which all of that MSA's banks are excluded from the sample. Splitting the sample in this fashion addresses a particular concern about a possible spurious relationship between market concentration and construction shares. This potential concern is that the observed negative relationship between concentration and construction lending may arise because banks in a market area where a competitor bank has failed react to the failure of their competitor by shifting away from risky lending, at the same time that concentration is increasing due to the failure of this competitor. Among the pre-failure sample, column (1) again shows a negative relationship between concentration and construction lending; in this sample a 500 point increase in the Herfindahl Index is associated with a 24 basis point drop in the construction lending share. Column (2), which adds MSA-specific trends, provides less support. With the inclusion of MSA-specific trends, in such a truncated sample, concentration has no statistically significant effect in any of the five regressions reported in Table 11.

Columns (3) through (6) of Table 11 assess the impact of changes in concentration among banks that maintain significant construction lending throughout the period. Changes in concentration may affect construction lending both on an extensive margin, affecting share of banks doing any construction lending at all, and on an intensive margin, affecting the intensity of construction lending among banks already active in this sector. Columns (3) through (6) focus on the intensive margin of the relationship between concentration and construction. Columns (3) and (4) focus on the 37196 bank-year observations with positive construction lending in every period of their observed existence, and columns (5) and (6) on the 34407 observations whose construction lending exceeds the entire-sample mean in each period. In each of these samples, the estimated coefficients are indistinguishable from the larger sample, suggesting that changes in concentration are active along this intensive margin.

### 1.6.3. Instrumental variables estimation of concentration and portfolio shares

Instrumental variables techniques provide another approach to evaluating the relationship between concentration and portfolio shares. IV techniques again regress portfolio shares on measures of concentration, but use only the part of variation in concentration that is statistically explained by a third set of variables, called instrumental variables. If these instruments affect the variation in portfolio shares only through their impact on concentration, then the result is an estimate that is not subject to concerns about bias from spurious correlation or reverse causation. The cost of these techniques is loss of precision, as well as bias if assumptions about the relationship between the instruments and the dependent variables are false.

Table 12 presents both the OLS results from Table 8 and the results of instrumental variables analysis for two different sets of instruments. The first instrument used is a dummy for the removal of restrictions on intra-state branching by merger with existing banks. The implicit assumption is that changes in branching restrictions affect portfolio shares only through their indirect impact on concentration, and not through any direct impact of their own. This assumption is somewhat suspect; recent work, especially by Jayaratne and Strahan (1998), has shown that a variety of changes in banking markets follow deregulation, especially the expansion of more efficient banks at the expense of their weaker competitors.

Columns (5) and (6) employ a different strategy, using instruments that are based on state-level political control. The underlying assumption is that different political parties are differentially hostile to deregulation and changes in banking market concentration, so changes in political control will affect changes in concentration. This assumption is consistent with the empirical model of branching deregulation in Kroszner and Strahan (1999). The key identifying assumption is that these changes in political control only affect portfolio shares through their impact on concentration. The set of political instruments includes dummies for current Democratic Party control of state governorships and lower and higher houses of government, as well as variables describing the share of years (post-1970) that these branches of government have been under Democratic Party control.

The IV regression results in columns (3) through (6) reflect the loss of precision that can accompany IV techniques. Nevertheless, the results are broadly consistent with a negative relationship between concentration and the share of construction lending. In particular, coefficients from columns (3) and (6) point to a negative relationship between concentration and the share of construction lending that is substantially stronger than the relationship documented in the previous subsections. Columns (4) and (5) show statistically insignificant (and highly imprecise) results. The enormous imprecision of column (4) reflects the addition of MSA-specific trends to an IV model with a dummy instrumental variable that turns "on" during the sample. Column (6), using political control instruments and including MSA-specific trends, suggests that a change in concentration of 250 Herfindahl Index points is associated with a greater than 1 percentage point change in the construction lending share. It seems implausible that such a strong relationship holds throughout the entire range of the concentration distribution; and is important to note that the previous subsection documented important nonlinearity in the relationship between concentration and construction lending. The instrumental variables techniques may be focusing empirical analysis on a region of the concentration distribution where construction lending is highly sensitive to concentration. Nevertheless, the results, on the whole, provide some support for a causal interpretation of the concentration-risky lending relationship.

### 1.6.4. Concentration and portfolio shares, before and after deregulation

In addition to changing observed concentration, many places in the 1980s saw the repeal of restrictions on banks' geographic expansion. As discussed earlier, the repeal of these restrictions exposed banking markets to potential competition, which can affect behavior even in markets that remain concentrated. In these deregulated markets, potential competition reduces the quality of observed concentration as a measure of the true competitiveness of the local market area. For example, when entry is restricted by regulation, a local monopolist can exploit its market power. With entry allowed, a bank that attempts to exploit its position as the sole bank in a market encourages entry from potential competitors. Thus, following deregulation and the repeal of branching restrictions, observed local market concentration becomes a less relevant measure of market power.

Table 13 reports regressions that separately estimate the impact of concentration before and after the repeal of branching restrictions. Equation (10) below gives the functional form for these regressions:

$$\begin{aligned}(10)\qquad SHR_{j,i,t}^{MSA} = \alpha + \beta^{R} &* HHI_t^{MSA} * NOBRANCH_t^{MSA} \\ &+ \beta^{NR} * HHI_t^{MSA} * (1\text{-}NOBRANCH_t^{MSA}) \\ &+ \delta * (1\text{-}NOBRANCH_t^{MSA}) + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}\end{aligned}$$

$NOBRANCH_t^{MSA}$ is a dummy variable equal to one for bank-year observations in periods when branching was restricted. The coefficient $\beta^R$ gives the slope of the concentration-portfolio relationship before the repeal of branching restrictions, the coefficient $\beta^{NR}$ gives the slope afterwards.

As Table 3 showed, different types of restrictions affected branching, and these barriers were generally lifted at different times. In most states, the legalization of branching by interstate multi-bank holding companies, the legalization of intra-state branching through the purchase of existing banks, and the legalization of "full branching" (where banks can open entirely new branches throughout the state) occurred in different years. A slightly different version of equation (10) corresponds to each type of branching restriction.

Columns (1) and (2) of Table 13 show regressions where the NOBRANCH variable identifies the periods before and after the legalization of branching by merger and assumption (corresponding to the second column of table 3); columns (3) and (4) correspond to de novo branching, and (5) and (6) correspond to interstate branching. Column (2) of Table 13 shows that prior to the repeal of branching restrictions, a 1000 point drop in the Herfindahl Index raised the expected value of the construction loan/total loan ratio by about 131 basis points. After deregulation, which may have reduced the link between concentration and market power, the same fall in Herfindahl Index raises the ratio by only 60 basis points. At a Herfindahl Index of 1902 [12], the repeal of branching restrictions seems to exert a very small net effect on the share of loans lent out to this sector.

The results in this section provide more evidence that the relationship between market concentration and the share of loans going to construction projects is causal, rather than reflecting either the influence of some unobserved third factor or reverse causation from portfolio choice to market concentration. In the period prior to the repeal of branching restrictions, when observed concentration is a better proxy for the true competitiveness of the local market area, the impact of concentration on portfolio choice is much greater than in the later periods, when potential competition from outsiders makes observed concentration a worse proxy for the competitiveness of the environment.

### 1.6.5. MSA-level regression analysis

The strongest and most regular result of the previous section was that increasing banking sector concentration reduces the flow of bank capital to construction loans. This section presents evidence that this relationship has a measurable real effect on macroeconomic variables at the MSA level: increases in MSA banking market concentration are associated with decreasing employment shares in both the real estate and construction sectors.

[12] This is the MSA-weighted sample mean.

A 15-year sample of 300 MSAs forms the basis for the analysis that follows. Bank-level observations of total loans, assets, and loan types are aggregated to the MSA level. Employment variables are constructed from Census County Business Pattern data; county-level employment observations are aggregated to the MSA level using the bank shares within each county. Table 14 documents sample statistics for this sample of 3000 MSA-year observations.

Table 15 details results from regression analysis at the level of the individual MSA. For the banking-sector variables, I run regressions such as equation (12) below, where the index j indexes the various banking sector balance sheet items:

(12) $SHR_{j,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

The first five rows of Table 15 show the results of regressions such as (12). At the aggregate level, there is still strong evidence that increasing banking sector concentration reduces the flow of capital to the commercial real estate sector, both as a share of banking assets and as a share of total loans. The results in columns (6) and (7) suggest that a 500 point increase in an MSA Herfindahl Index is associated with a 50 basis point increase in the aggregate share of loans going to construction projects. The evidence on total loans is broadly similar to the analysis at the bank level in the preceding subsections. While in regressions without controls and with only year dummies, increasing concentration is significantly and positively associated with total loans as a share of assets, adding MSA fixed effects makes the estimated coefficient statistically insignificant. Again, adding MSA-specific trends changes the sign of the observed relationship. How this reflects the impact of concentration changes along different horizons is an open question of research.

The results above suggest a relationship between concentration and aggregate lending shares: changes in concentration are associated with shifting bank activity toward construction lending. I now assess whether there is evidence of a relationship between local market concentration and the share of employment in sectors that are sensitive to construction activity. I use annual Census County Business Pattern data, aggregated to MSA level, which breaks out employment to the 2-digit SIC code level. I focus in particular on the share of MSA employment in construction and real estate sectors, two sectors particularly sensitive to bank construction lending activity. The final two rows of Table 15 document the results of this exercise. For real estate employment as a share of total employment, a 500 Herfindahl point increase in concentration is associated with a 4 basis point drop in real estate employment, or about 3.1 percent of the sample mean. For construction employment, the result in column (7) suggests that the same concentration change is associated with a 10 basis point drop in construction employment, or about 1.8 percent of the sample mean. While these estimated impacts are not huge, they are consistent with shifts in bank capital having some impact on aggregate macroeconomic activity.

### 1.7. Implications for the FDIC

Because the Federal Deposit Insurance Corporation stands ready to assume the assets and liabilities of failing banking institutions, the impact of concentration on banks' demand for the riskiest of assets that they hold has implications for the FDIC's implicit liability to the banking sector, and thus on the financial position of the federal government. The following section uses the analysis of the previous sections to estimate the impact of changing concentration on the implicit liability of the FDIC.

The aggregate direct cost of bank failure to the FDIC is the product of the number of banks failing and the cost to the FDIC of each failure. The regression results reported in Table 16 are designed to assess the relationship between market structure and the probability of eventual bank failure. The first three columns of Table 16 report the results a linear probability model fit separately in each year of the sample, with the dependent variable equal to one if the bank observed in that year will eventually fail. These models are based on equation (13) below:

(13) $\mathrm{I}(\textit{ever fail})_{i,t}^{MSA} = \alpha + \beta * \mathrm{HHI}_t^{MSA} + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}$

The final column of the table gives the share of these banks that will eventually fail; this share ranges from a high of 10.27 percent in 1984 to a low of 0.39 percent in the final year of the sample. The first column fits equation (13) with no controls, the second includes controls for the nine census regions, and the third column includes controls for region, individual bank size, and the size of the MSA in which the bank is headquartered. The next three columns of Table 16 report regressions based on data aggregated to the MSA level. These models fit equation (14) below:

(14) $\text{SHR\_BANKS\_EVER\_FAIL}_t^{MSA} = \alpha + \beta * \text{HHI}_t^{MSA} + X_t^{MSA}\,\Gamma + \varepsilon_t$

As in the first three columns, the first column has no controls, the second column has nine controls for the census regions, and the third column has controls for MSA size. Table 16 suggests a relationship between market structure and the probability of bank failure, driven by the spate of bank failures during the 1980s. In 1980, across MSAs, a 500 point increase in an MSA's Herfindahl Index is associated with a 0.96 percent reduction in the share of banks in that MSA that eventually fail. Reflecting the reduction in the rate of bank failure since then, regressions fit on data after about 1990 show no relatiohsip between market structure and failure probability.

Table 17 reports the results of regressions that pool observations over time. The first row reports regression results based on equation (15):

(15) $I(\textit{fail in next year})_{i,t}^{MSA} = \alpha + \beta * \text{HHI}_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

Reading across the rows in Table 17 gives the coefficient on the concentration measure for different sets of control variables. The estimated coefficient rates from 0.07 (standard error 0.15) in a regression with only MSA dummy variables to -0.37 (0.26) in a regression with year and MSA effects and MSA trends. The next row in Table 17 fits regressions of equation (16) below:

(16) $I(\textit{fail in next 4 years})_{i,t}^{MSA} = \alpha + \beta * \text{HHI}_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

Reading across the row, we see that in the sample, an increase of 1000 points in the Herfindahl Index is associated with between a 0.46 and 2.97 percent reduction in the probability of failure in the next 4 years for the banks in the sample. The weakest estimated effect comes in a regression that includes separate region dummy variables for each year. A regression that includes MSA fixed effects, year fixed effects, and MSA-specific trends finds the largest estimated effect. The final row of Table 17 shows the results of estimating equation (17) below with a varying set of control variables:

(17) $I(\textit{ever fail})_{i,t}^{MSA} = \alpha + \beta * \text{HHI}_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

In the sample, an increase of 1000 Herfindahl Index points is associated with between a 0.70 and 2.71 percent reduction in the probability of eventual bank failure. In the regression that includes MSA and year fixed effects, as well as MSA-specific trend variables, the coefficient on the Herfindahl Index of –2.00. This implies that a 500 Herfindahl Index point increase in concentration is associated with a 1 percent decrease in the probability of eventual failure.

The second panel of Table 17 reports regressions based on observations aggregated to the MSA level. The first row of the second panel fits equation (18) below with varying sets of control variables:

(18) $SHR\_BANKS\_FAIL\_NEXTYEAR_t^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

The next two rows in the panel fit similar regressions, where the share variables are the share of banks that fail in the next four years and the share that fail ever. Not surprisingly, the results are consistent with the results in the first panel and imply that an increase in concentration of 1000 Herfindahl Index points is associated with an reduction in the share of banks failing of between 1.28 and 1.96 percentage points.

Aggregating to the MSA level permits me to assess not just the relationship between the share of banks failing and concentration but the relationship between the share of assets held at banks that will fail and concentration. This analysis goes further toward providing an estimate of the direct costs from liquidation of failing banks to the FDIC. The first row in this sequence estimates equation (19) below:

(19) $SHR\_ASSETS\_FAIL\_NEXTYEAR_t^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

While the next two columns estimate two additional models, equation (20):

(20) $SHR\_ASSETS\_FAIL\_NEXT\_4\_YEARS_t^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

where the dependent variable is the share of assets at banks that fail within four years, and equation (21):

(21) $SHR\_ASSETS\_FAIL\_EVER_t^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\,\Gamma + \varepsilon_t^{MSA}$

where the dependent variable is the share of assets and banks that fail ever.

The differences across the columns regressions come from the set of control variables added to the regression. For example, column (4) suggests that an increase of 1000 Herfindahl Index points is associated with a 0.23 percent decrease in the share of assets held at banks that will fail in the next year, a 1.10 percent decrease in the share of assets held at banks that will fail in the next four years, and a 1.95 percent decrease in the share of assets held at banks that will fail ever. Column (7), which controls for

MSA and year fixed effects, as well as MSA-specific trends, suggests that an increase of 500 Herfindahl Index points is associated with a 0.73 percent decrease in the share of assets held at banks that will fail ever.

This empirical estimate is an important input to an assessment of the relationship between market structure and the implicit liability from the FDIC to bank depositors. Moving from one to the other requires an assessment of the share of assets that are lost in the bank failures. James (1991) estimates that costs to the FDIC from bank failures amount to approximately one third of the value of assets of failing banks. Losses on the banks' portfolios of assets amounts to about 30 percent of assets, and these losses are primarily related to the recognition of past unrealized losses. An additional 10 percent comes from the administrative and legal costs of executing the transaction.

Matching James' estimate of the costs to the FDIC of bank failure with my empirical estimate from column (7) of Table 17 suggests that a change in market concentration of 500 Herfindahl Index points is associated with a 500* -1.45 = 0.73 percent decrease in the share of assets held at banks that will fail, at a cost to the FDIC of 0.73*0.40 = 0.29 percent of insured assets in the banking sector. With approximately $5 trillion in assets in the banking system, an increase in the Herfindahl Index of 100 points in each market would be associated with a cost to the FDIC of $2.9 billion dollars. This estimate assumes that changes in market structure do not affect the "severity" of failure, conditional on market failure. If the reductions in market concentration also increase the cost of resolution conditional on failure, then the figure above underestimates the impact of changes in market structure on the FDIC's implicit liability.

**1.8. Conclusion**

There is strong evidence that increasing concentration has been associated with reductions in the flow of bank capital to construction and land development loans, which are the highest-risk category of commercial bank loans. Robustness to a variety of control and instrumental variables strategies supports a causal interpretation of this empirical relationship. The magnitude of this effect is large: an increase in concentration from the $25^{th}$ to the $75^{th}$ percentile is associated with a 20 percent drop in the share of bank lending going to construction loans. Increasing concentration also appears to increase average bank capitalization, raise the average share of assets loaned out to borrowers, and reduce bank failure rates during this period. Because the Federal Deposit Insurance Corporation stands ready to assume the assets and liabilities of failing banks, changes in bank portfolio risk affect the value of the government's contingent liability to the banking sector, as well as the health and stability of the financial sector and the larger economy.

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Table 1.
Local commercial bank deposit Herfindahl-Hirschman indexes, by MSA. Herfindahl-Hirschman Index (HHI) figures are computed from the sum of the squared market shares within a local market area according to the formula HHI = $10000*\Sigma s_i^2$ ,where $s_i$ is the share of a local market's deposits held at bank i. Data provided by Phil Strahan

| Year | Number of MSAs | Mean | Standard Deviation | Percentiles 25th | 50th | 75th | Mean Asset-weighted | Mean Bank-weighted |
|---|---|---|---|---|---|---|---|---|
| | | MSA-weighted | | | | | | |
| 1980 | 200 | 1884.4 | 806.5 | 1272.7 | 1736.2 | 2400.0 | 1680.4 | 1403.8 |
| 1981 | 200 | 1872.7 | 797.5 | 1280.3 | 1740.7 | 2419.5 | 1762.2 | 1413.9 |
| 1982 | 200 | 1852.4 | 803.5 | 1268.3 | 1684.1 | 2395.8 | 1730.9 | 1398.6 |
| 1983 | 200 | 1842.1 | 788.0 | 1256.5 | 1714.8 | 2292.8 | 1667.0 | 1403.6 |
| 1984 | 200 | 1894.4 | 768.1 | 1315.6 | 1766.0 | 2310.4 | 1642.3 | 1442.8 |
| 1985 | 200 | 1891.7 | 772.2 | 1287.9 | 1768.7 | 2304.9 | 1601.7 | 1412.9 |
| 1986 | 200 | 1980.4 | 778.8 | 1428.1 | 1882.0 | 2384.7 | 1683.2 | 1483.4 |
| 1987 | 200 | 1982.2 | 749.2 | 1426.6 | 1862.9 | 2373.5 | 1672.0 | 1522.5 |
| 1988 | 200 | 1916.1 | 761.9 | 1355.4 | 1819.1 | 2326.9 | 1597.0 | 1421.7 |
| 1989 | 200 | 1905.6 | 730.7 | 1332.4 | 1796.0 | 2338.6 | 1600.8 | 1452.4 |
| 1990 | 200 | 1914.5 | 709.4 | 1384.4 | 1810.5 | 2359.5 | 1615.0 | 1479.8 |
| 1991 | 200 | 1868.8 | 701.2 | 1364.8 | 1747.8 | 2235.1 | 1610.1 | 1432.0 |
| 1992 | 200 | 1907.8 | 722.2 | 1423.1 | 1772.1 | 2318.2 | 1691.0 | 1475.9 |
| 1993 | 200 | 1887.4 | 661.9 | 1422.4 | 1821.3 | 2232.0 | 1728.6 | 1493.7 |
| 1994 | 200 | 1925.2 | 666.9 | 1451.8 | 1784.0 | 2234.2 | 1778.7 | 1554.5 |
| All years | 3000 | 1901.7 | 748.5 | 1353.3 | 1782.9 | 2322.8 | 1670.3 | 1449.5 |

Table 2.
Distribution of changes in local commercial bank deposit Herfindahl-Hirschman Indexes, 1980-1994. Data provided by Phil Strahan.

| | Unweighted | Weighted by MSA deposits |
|---|---|---|
| Mean | 40.8 | 54.3 |
| Standard Deviation | 588.9 | 505.8 |
| *Percentiles* | | |
| $10^{th}$ | -709.2 | -510.0 |
| $25^{th}$ | -257.9 | -228.9 |
| $50^{th}$ | 42.6 | 63.2 |
| $75^{th}$ | 386.6 | 385.2 |
| $90^{th}$ | 831.5 | 724.8 |
| Inter-quartile range | 644.5 | 614.1 |

Table 3.
Deregulation of branching restrictions, 1980-1994. Figure in each cell shows the number of states that have by year listed in row allowed banks to branch according to the means listed in the column headings. Data provided by Phil Strahan.

| | Number of states that allow branching | | | |
|---|---|---|---|---|
| Year | Through multi-bank holding companies (MBHC) | By merger and assumption (M&A) | Full branching (De novo) | By interstate bank holding companies (Interstate) |
| 1980 | 38 | 19 | 15 | 1 |
| 1981 | 39 | 21 | 16 | 1 |
| 1982 | 42 | 22 | 16 | 3 |
| 1983 | 44 | 23 | 16 | 5 |
| 1984 | 46 | 24 | 17 | 8 |
| 1985 | 50 | 28 | 19 | 18 |
| 1986 | 50 | 30 | 20 | 28 |
| 1987 | 50 | 35 | 23 | 37 |
| 1988 | 50 | 41 | 28 | 43 |
| 1989 | 50 | 42 | 30 | 45 |
| 1990 | 51 | 46 | 36 | 46 |
| 1991 | 51 | 48 | 38 | 48 |
| 1992 | 51 | 48 | 38 | 49 |
| 1993 | 51 | 49 | 39 | 50 |
| 1994 | 51 | 50 | 39 | 50 |

Table 4.
Descriptive statistics for sample of bank-year observations, 1980-1994. Data come from 1980-1994 fourth-quarter FDIC Reports of Condition and Income. These data are available at the Chicago Fed website, http://www.chicagofed.org.

| Variable | % > 0 | Mean | Stand. Dev. | Percentiles 10th | 25th | 50th | 75th | 90th |
|---|---|---|---|---|---|---|---|---|
| *Bank size* | | | | | | | | |
| Assets | 100.0 | 367.6 | 2375.3 | 13.8 | 26.0 | 55.7 | 136.2 | 410.8 |
| Total loans | 100.0 | 226.6 | 1595.7 | 6.7 | 13.6 | 30.3 | 77.2 | 238.5 |
| Deposits | 99.9 | 283.8 | 1825.7 | 11.7 | 22.8 | 49.0 | 118.8 | 341.1 |
| *Portfolio characteristics* | | | | | | | | |
| Total loans /Assets | 100.0 | 0.561 | 0.149 | 0.367 | 0.475 | 0.574 | 0.659 | 0.730 |
| Construction loans /Assets | 80.6 | 0.028 | 0.042 | 0.000 | 0.002 | 0.013 | 0.036 | 0.074 |
| Construction loans /Total loans | 80.6 | 0.047 | 0.066 | 0.000 | 0.003 | 0.023 | 0.062 | 0.123 |
| Commercial loans /Assets | 97.9 | 0.141 | 0.100 | 0.031 | 0.066 | 0.122 | 0.194 | 0.277 |
| Home mortgage loans /Assets | 97.8 | 0.135 | 0.104 | 0.027 | 0.062 | 0.115 | 0.184 | 0.262 |
| Nonresidential mortgage loans /Assets | 93.1 | 0.073 | 0.066 | 0.005 | 0.025 | 0.057 | 0.102 | 0.156 |
| Consumer loans /Assets | 99.3 | 0.129 | 0.109 | 0.033 | 0.062 | 0.106 | 0.167 | 0.241 |
| Net Liquid Assets /Assets | 98.9 | 0.372 | 0.168 | 0.171 | 0.270 | 0.366 | 0.474 | 0.584 |
| Cash /Assets | 100.0 | 0.095 | 0.069 | 0.037 | 0.053 | 0.076 | 0.115 | 0.173 |
| Nonperforming loans /Assets | 67.2 | 0.008 | 0.014 | 0.000 | 0.000 | 0.003 | 0.010 | 0.021 |
| Equity /Assets | 99.6 | 0.089 | 0.062 | 0.056 | 0.066 | 0.078 | 0.095 | 0.124 |
| Herfindahl-Hirschman Index (HHI) | 100.0 | 1449.5 | 616.8 | 777.4 | 988.9 | 1332.1 | 1794.2 | 2266.4 |

Table 5.
Commercial bank failure rates, 1980-1994. Data come from FDIC Call Reports.

| | | Share of banks failing | | | |
|---|---|---|---|---|---|
| | | Unweighted | | | Weighted by assets |
| Year | Number of banks | Next year | Next 2 years | Ever | Ever |
| 1980 | 5147 | 0.08 | 0.25 | 8.22 | 6.16 |
| 1981 | 5114 | 0.18 | 0.47 | 8.56 | 6.89 |
| 1982 | 5159 | 0.29 | 0.60 | 9.09 | 7.06 |
| 1983 | 5015 | 0.36 | 0.86 | 9.59 | 6.83 |
| 1984 | 5142 | 0.47 | 1.32 | 10.27 | 7.27 |
| 1985 | 5166 | 0.77 | 2.19 | 10.22 | 6.98 |
| 1986 | 5156 | 1.40 | 3.55 | 9.76 | 6.41 |
| 1987 | 4878 | 2.13 | 4.80 | 8.90 | 6.59 |
| 1988 | 4583 | 2.64 | 4.60 | 7.16 | 4.48 |
| 1989 | 4422 | 1.94 | 2.94 | 4.79 | 3.74 |
| 1990 | 4268 | 0.98 | 1.99 | 2.98 | 2.82 |
| 1991 | 4077 | 1.01 | 1.55 | 2.04 | 0.70 |
| 1992 | 4145 | 0.55 | 0.70 | 1.04 | 0.17 |
| 1993 | 3840 | 0.13 | 0.23 | 0.49 | 0.08 |
| 1994 | 3636 | 0.11 | 0.17 | 0.39 | 0.04 |

Table 6.
Characteristics of failing and surviving banks. Data come from FDIC Call Reports.

| | | All banks | | Banks that fail eventually | | Banks that do not fail | |
|---|---|---|---|---|---|---|---|
| Characteristic | Year | Count | Mean | Percent of total | Mean | Percent of total | Mean |
| Equity /Assets | 1980 | 5147 | 0.091 | 8.2 | 0.092 | 91.8 | 0.089 |
| | 1985 | 5166 | 0.088 | 10.2 | 0.089 | 89.8 | 0.082 |
| | 1990 | 4268 | 0.088 | 3.0 | 0.089 | 97.0 | 0.049 |
| Construction loans/Assets | 1980 | 5149 | 0.018 | 8.2 | 0.030 | 91.8 | 0.017 |
| | 1985 | 5170 | 0.032 | 10.2 | 0.060 | 89.8 | 0.029 |
| | 1990 | 4280 | 0.032 | 3.0 | 0.063 | 97.0 | 0.031 |
| Construction loans/Total loans | 1980 | 5149 | 0.033 | 8.2 | 0.055 | 91.8 | 0.031 |
| | 1985 | 5170 | 0.051 | 10.2 | 0.089 | 89.8 | 0.047 |
| | 1990 | 4280 | 0.052 | 3.0 | 0.092 | 97.0 | 0.051 |

Table 7.
Contribution of portfolio components to bank failure probabilities. Each row shows estimated coefficients based on equation (8): $I(ever\ fail)_{i,t}^{MSA} = \alpha + \Sigma\ \beta_1 * SHR_{j,i,t}^{MSA} + \varepsilon_{i,t}$, where $I(ever\ fail)_{i,t}^{MSA}$ is an indicator variable set equal to 1 if bank i, observed at time t, eventually fails, and $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets at time t, held in asset class j (asset classes are listed along the column headings). Equation (8) is estimated separately for each year. Data come from fourth quarter FDIC Call Reports. Number of observations ranges from 5166 to 3636.

| year | Net liquid assets /Assets | Home mortgage loans /Assets | Non-residential mortgage loans /Assets | Construction loans /Assets | Commercial loans /Assets | Consumer loans /Assets | $R^2$ (n) | Share of banks eventually failing |
|---|---|---|---|---|---|---|---|---|
| 1980-1994 pool | -0.069* (0.019) | -0.094* (0.022) | 0.070* (0.035) | 0.644* (0.074) | 0.297* (0.030) | 0.046* (0.023 | 0.067 (69748) | 6.64% |
| 1980 | 0.016 (0.040) | -0.295* (0.049) | -0.231* (0.092) | 0.883* (0.133) | 0.299* (0.052) | 0.079 (0.044) | 0.044 (5147) | 8.22% |
| 1981 | -0.036 (0.038) | -0.245* (0.046) | -0.281* (0.095) | 1.055* (0.140) | 0.334* (0.048) | 0.093 (0.048) | 0.053 (5114) | 8.56 |
| 1982 | -0.076 (0.046) | -0.160* (0.057) | -0.156 (0.102) | 1.045* (0.134) | 0.391* (0.056) | 0.071 (0.052) | 0.060 (5159) | 9.09 |
| 1983 | -0.027 (0.046) | -0.077 (0.059) | -0.008 (0.099) | 1.284* (0.115) | 0.447* (0.056) | 0.062 (0.055) | 0.072 (5015) | 9.59 |
| 1984 | -0.015 (0.045) | -0.066 (0.059) | 0.262* (0.091) | 1.125* (0.096) | 0.482* (0.057) | 0.086 (0.054) | 0.081 (5142) | 10.27 |
| 1985 | -0.019 (0.045) | 0.051 (0.057) | 0.443* (0.084) | 1.021* (0.100) | 0.549* (0.057) | 0.146* (0.054) | 0.085 (5166) | 10.22 |
| 1986 | -0.055 (0.045) | 0.029 (0.056) | 0.394* (0.078) | 0.839* (0.097) | 0.509* (0.057) | 0.136* (0.054) | 0.072 (5156) | 9.76 |
| 1987 | -0.129* (0.046) | -0.109* (0.054) | 0.357* (0.074) | 0.489* (0.097) | 0.316* (0.059) | 0.013 (0.053) | 0.056 (4878) | 8.90 |
| 1988 | -0.139* (0.046) | -0.196* (0.050) | 0.296* (0.069) | 0.289* (0.090) | 0.151* (0.055) | -0.040 (0.050) | 0.039 (4583) | 7.16 |
| 1989 | -0.051 (0.035) | -0.074 (0.041) | 0.133* (0.055) | 0.347* (0.074) | 0.106* (0.047) | 0.002 (0.041) | 0.021 (4422) | 4.79 |
| 1990 | 0.000 (0.029) | -0.010 (0.033) | 0.121* (0.045) | 0.341* (0.062) | 0.098* (0.039) | 0.019 (0.034) | 0.019 (4268) | 2.98 |
| 1991 | -0.005 (0.025) | -0.028 (0.028) | 0.061 (0.036) | 0.394* (0.059) | 0.048 (0.034) | 0.013 (0.029) | 0.020 (4077) | 2.04 |
| 1992 | -0.024 (0.018) | -0.004 (0.021) | 0.011 (0.026) | 0.295* (0.046) | 0.017 (0.026) | -0.017 (0.022) | 0.019 (4145) | 1.04 |
| 1993 | 0.021 (0.012) | -0.003 (0.011) | 0.035* (0.014) | 0.084* (0.031) | 0.033* (0.015) | 0.009 (0.011) | 0.008 (3840) | 0.49 |
| 1994 | -0.004 (0.010) | -0.011 (0.013) | 0.017 (0.015) | -0.016 (0.027) | 0.020 (0.017) | -0.001 (0.013) | 0.003 (3636) | 0.39 |

Table 8.

Regressions of portfolio shares on local commercial banking market concentration. Entries in table show regression coefficient on MSA Herfindahl Index in equation (9): $SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Fixed effects | None | None | Year | Region by year | MSA | MSA, year | MSA, year |
| Controls | None | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | None | None | None | None | None | MSA |
| *Dependent variable* | | | | | | | |
| Total loans | 1.72* | 2.07* | 1.91* | 0.74* | 1.47* | 1.64* | -0.92* |
| /Assets | (0.23) | (0.25) | (0.25) | (0.25) | (0.36) | (0.38) | (0.37) |
| Construction loans | -0.07 | 0.08 | 0.04 | -0.14* | -0.67* | -0.65* | -0.77* |
| /Assets | (0.05) | (0.06) | (0.06) | (0.06) | (0.09) | (0.09) | (0.12) |
| Construction loans | -0.26* | -0.06 | -0.13 | -0.27* | -1.03* | -1.03* | -1.00* |
| /Total loans | (0.09) | (0.09) | (0.09) | (0.09) | (0.14) | (0.14) | (0.18) |
| Liquid assets | -2.15* | -2.63* | -1.96* | -0.91* | -2.92* | -1.48* | 1.19* |
| /Assets | (0.25) | (0.26) | (0.26) | (0.27) | (0.38) | (0.36) | (0.39) |
| Equity | 0.21* | 0.22* | 0.23* | 0.03 | 0.63* | 0.81* | 0.73* |
| /Assets | (0.08) | (0.08) | (0.09) | (0.09) | (0.14) | (0.15) | (0.18) |

Table 9.
Regressions of portfolio shares on local commercial banking market concentration, selected samples of banks. Entries in table show regression coefficient on MSA Herfindahl Index in equation (9): $SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | Small, never-merging banks (N=19663) | | Well-capitalized banks (N=31318) | | Poorly-capitalized banks (N=37932) | |
| Fixed effects | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | MSA | None | MSA | None | MSA |
| *Dependent variable* | | | | | | |
| Total loans /Assets | 0.40<br>(0.71) | -2.03*<br>(0.67) | 1.26*<br>(0.53) | -1.28*<br>(0.60) | 2.26*<br>(0.47) | -0.44<br>(0.50) |
| Construction loans /Assets | -0.76*<br>(0.17) | -0.94*<br>(0.21) | -0.47*<br>(0.13) | -0.50*<br>(0.18) | -0.74*<br>(0.13) | -0.92*<br>(0.18) |
| Construction loans /Total loans | -1.23*<br>(0.26) | -1.32*<br>(0.32) | -0.74*<br>(0.20) | -0.59*<br>(0.26) | -1.20*<br>(0.19) | -1.21*<br>(0.26) |
| Liquid assets /Assets | -0.23<br>(0.66) | 2.65*<br>(0.67) | -1.55*<br>(0.50) | 1.45*<br>(0.63) | -2.12*<br>(0.47) | 0.74<br>(0.56) |
| Equity /Assets | 0.85*<br>(0.30) | 1.05*<br>(0.38) | 0.94*<br>(0.26) | 1.19*<br>(0.34) | 0.13<br>(0.59) | 0.34<br>(0.07) |

Table 10.
Regressions of portfolio shares on local commercial banking market concentration, selected samples of MSAs. Entries in table show regression coefficient on MSA Herfindahl Index in equation (9): $SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Sample | MSAs with increases in concentration (N=40766) | | MSAs with decreases in concentration (N=28484) | | Excluding least concentrated MSA-year observations (N=50479) | | Least concentrated (HHI < 1000) MSA year observations (18771) | |
| Fixed effects | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | MSA | None | MSA | None | MSA | None | MSA |
| *Dependent variable* | | | | | | | | |
| Total loans /Assets | 3.70* (0.47) | 0.16 (0.47) | -2.47* (0.64) | -2.38* (0.62) | 0.02 (0.42) | -1.14* (0.40) | 9.83* (1.08) | 0.49 (1.94) |
| Construction loans /Assets | -0.68* (0.14) | -0.72* (0.16) | -0.91* (0.17) | -0.84* (0.19) | -0.94* (0.11) | -1.24* (0.28) | 1.07* (0.29) | 0.72 (0.44) |
| Construction loans/Total loans | -1.11* (0.21) | -0.97* (0.24) | -1.21* (0.25) | -1.06* (0.27) | -1.35* (0.16) | -1.24* (0.19) | 0.92* (0.47) | 0.83 (0.69) |
| Liquid assets /Assets | -4.17* (0.45) | 0.28 (0.50) | 2.27* (0.65) | 2.37* (0.70) | -0.31 (0.41) | 1.22* (0.42) | -9.04* (1.11) | 0.32 (2.16) |
| Equity /Assets | 1.24* (0.20) | 0.74* (0.20) | 0.88* (0.28) | 0.73* (0.33) | 0.56* (0.16) | 0.86* (0.18) | 1.59* (0.49) | 0.05 (0.86) |

Table 11.

Regressions of portfolio shares on local commercial banking market concentration, selected samples of banks. Entries in table show regression coefficient on MSA Herfindahl Index in equation (9): $SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | MSAs where no banks have failed yet (N=34630) | | Banks with positive construction lending in all periods (N=37196) | | Banks with above-mean construction lending in all periods (N=34407) | |
| Fixed effects | MSA, Year | MSA, Year | MSA, Year | MSA, Year | MSA, Year | MSA, Year |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | MSA | None | MSA | None | MSA |
| *Dependent variable* | | | | | | |
| Total loans | 0.87* | -0.47 | 1.52* | 0.06 | 1.36* | 0.27 |
| /Assets | (0.49) | (0.56) | (0.44) | (0.41) | (0.45) | (0.42) |
| Construction loans | -0.35* | -0.20 | -0.73* | -0.82* | -0.79* | -0.84* |
| /Assets | (0.12) | (0.17) | (0.13) | (0.18) | (0.14) | (0.19) |
| Construction loans | -0.48* | -0.12 | -1.10* | -1.08* | -1.17* | -1.09* |
| /Total loans | (0.18) | (0.24) | (0.20) | (0.25) | (0.22) | (0.27) |
| Liquid assets | -1.30* | -0.09 | -1.62* | -0.08 | -1.44* | -0.40* |
| /Assets | (0.51) | (0.64) | (0.43) | (0.43) | (0.45) | (0.44) |
| Equity | 0.79* | -0.06 | 0.59* | 0.63* | 0.61* | 0.67* |
| /Assets | (0.23) | (0.28) | (0.12) | (0.15) | (0.13) | (0.16) |

Table 12.
Instrumental variable regressions of portfolio shares on local commercial banking market concentration. Entries in table show regression coefficient on MSA Herfindahl Index in equation (9): $SHR_{j,i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering. Increment to $R^2$ from adding branching deregulation instruments to first stage regression is 0.0182. For state political control variables, increment to $R^2$ is 0.0469.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Instruments for concentration | None (OLS) | | Intrastate branching deregulation (IV) | | State political party variables (IV) | |
| Fixed effects | MSA, Year | MSA, Year | MSA, Year | MSA, Year | MSA, Year | MSA, Year |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | MSA | None | MSA | None | MSA |
| *Dependent variable* | | | | | | |
| Total loans /Assets | 1.64* | -0.92* | -13.81* | 139.48 | 11.72* | -17.69* |
| | (0.38) | (0.37) | (2.59) | (92.00) | (2.05) | (4.70) |
| Construction loans /Assets | -0.65* | -0.77* | -4.05* | 7.93 | 0.52 | -3.65* |
| | (0.09) | (0.12) | (0.69) | (12.95) | (0.46) | (0.90) |
| Construction loans /Total loans | -1.03* | -1.00* | -5.58* | 1.11 | -0.20 | -5.43* |
| | (0.14) | (0.18) | (1.06) | (18.35) | (0.72) | (1.36) |
| Liquid assets /Assets | -1.48* | 1.19* | 1.94 | -88.36 | -13.02* | 21.81* |
| | (0.36) | (0.39) | (2.46) | (66.11) | (2.17) | (4.83) |
| Equity /Assets | 0.81* | 0.73* | 2.27* | -15.55 | 5.63* | 3.60* |
| | (0.15) | (0.18) | (1.01) | (19.80) | (0.98) | (1.70) |

Table 13.
Regressions of portfolio shares on market concentration, before and after deregulation. Entries in table show regression coefficients $\beta^R$, $\beta^{NR}$, and $\delta$ from equation (11): $SHR_{j,i,t}^{MSA} = \alpha + \beta^R * HHI_t^{MSA} * NOBRANCH_t^{MSA} + \beta^{NR} * HHI_t^{MSA} * (1 - NOBRANCH_t^{MSA}) + \delta * (1 - NOBRANCH_t^{MSA}) + X_{i,t}^{MSA}\,\Gamma + \varepsilon_{i,t}^{MSA}$, where $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets (or loans), at time t, held in asset class j. The vector of controls $X_{i,t}^{MSA}$ includes bank and MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. All regressions include controls including bank and MSA size, (predicted) MSA employment growth, and the concentration of employment shares in the MSA. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Branching deregulation measure | Intrastate branching by merger allowed | | Intrastate de novo branching allowed | | Interstate branching allowed | |
| Fixed effects | None | MSA, year | None | MSA, year | None | MSA, year |
| *Dependent variable* | | | | | | |
| Construction Loans/Assets | | | | | | |
| HHI*NOBRANCH | -0.38* | -0.88* | -0.30* | -0.71* | -0.11 | -0.94* |
| | (0.06) | (0.09) | (0.06) | (0.09) | (0.06) | (0.10) |
| HHI*(1-NOBRANCH) | 0.31* | -0.30* | 0.25* | -0.25* | 0.26* | -0.19 |
| | (0.08) | (0.11) | (0.11) | (0.12) | (0.08) | (0.09) |
| NOBRANCH | 0.21 | 1.20* | -0.47* | 1.12* | 0.12 | 1.00* |
| | (0.15) | (0.13) | (0.21) | (0.15) | (0.13) | (0.12) |
| Change in ratio with deregulation at mean HHI | 1.09 | -0.19 | 1.52 | -0.26 | 0.58 | 0.44 |
| Construction Loans/Total Loans | | | | | | |
| HHI*NOBRANCH | -0.70* | -1.31* | -0.61* | -1.08* | -0.31* | -1.41* |
| | (0.10) | (0.15) | (0.09) | (0.14) | (0.10) | (0.16) |
| HHI*(1-NOBRANCH) | 0.27* | -0.60* | 0.24 | -0.51* | 0.16 | -0.44* |
| | (0.13) | (0.16) | (0.17) | (0.18) | (0.12) | (0.15) |
| NOBRANCH | 0.33 | 1.50* | -0.50 | 1.53* | 0.08 | 1.12* |
| | (0.24) | (0.21) | (0.32) | (0.24) | (0.20) | (0.20) |
| Change in ratio | 1.51 | -0.28 | 2.12 | -0.54 | 0.81 | 0.68 |

Table 14.
Sample statistics for data aggregated to MSA level. Data from fourth quarter FDIC Call Reports, 1980-1994; MSA totals constructed by summing individual bank observations. Employment data from Census County Business Patterns, available at http://fisher.lib.virginia.edu.

| | | Standard | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| Variable | Mean | deviation | 10th | 25th | 50th | 75th | 90th |
| *Banking sector size* | | | | | | | |
| Assets | 8547.0 | 20776.4 | 449.1 | 940.7 | 2125.9 | 5995.1 | 21926.9 |
| Total Loans | 5268.2 | 13671.6 | 251.0 | 510.4 | 1208.5 | 3469.9 | 13353.5 |
| Deposits | 6597.2 | 15926.8 | 388.8 | 811.2 | 1829.9 | 4904.1 | 16165.8 |
| *Aggregate bank portfolio characteristics* | | | | | | | |
| Total loans /Assets | 0.579 | 0.087 | 0.467 | 0.521 | 0.579 | 0.636 | 0.685 |
| Construction loans /Assets | 0.028 | 0.026 | 0.005 | 0.010 | 0.021 | 0.038 | 0.061 |
| Construction loans/ Total loans | 0.047 | 0.040 | 0.009 | 0.019 | 0.036 | 0.065 | 0.098 |
| Liquid assets /Assets | 0.314 | 0.123 | 0.158 | 0.254 | 0.327 | 0.393 | 0.456 |
| Equity /Assets | 0.074 | 0.015 | 0.058 | 0.065 | 0.073 | 0.081 | 0.090 |
| *MSA employment statistics* | | | | | | | |
| Real estate employment /Total employment | 0.013 | 0.007 | 0.006 | 0.008 | 0.012 | 0.016 | 0.021 |
| Constr. Employment /Total employment | 0.060 | 0.045 | 0.033 | 0.041 | 0.053 | 0.070 | 0.091 |

Table 15.
MSA-level regressions of portfolio shares on market concentration. Entries in table show regression coefficient on MSA Herfindahl Index in equation (12): $SHR_{j,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\, \Gamma + \varepsilon_t^{MSA}$ where $SHR_{j,t}^{MSA}$ is the share of the MSA's banking sector assets (or loans), at time t, held in asset class j. The vector of controls $X_t^{MSA}$ includes MSA size, MSA employment growth (predicted using lagged MSA employment shares at 2-digit SIC level and national growth rates in employment for those 2-digit SIC level employment components), and the concentration (measured by Herfindahl Index) of employment shares in the MSA. Data come from fourth quarter FDIC Call Reports, 1980-1994; MSA totals constructed by summing individual bank observations. Employment data from Census County Business Patterns, available at http://fisher.lib.virginia.edu.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Fixed effects | No | No | Year | Region by year | MSA | MSA, year | MSA, year |
| Controls | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | None | None | None | None | None | MSA |
| *Dependent variable* | | | | | | | |
| Total Loans | 0.77* | 1.24* | 1.07* | 0.36* | 0.91* | 0.25 | -1.65* |
| /Assets | (0.21) | (0.21) | (0.21) | (0.18) | (0.43) | (0.40) | (0.43) |
| Construction loans | -0.47* | -0.34* | -0.37* | -0.43* | -0.56* | -0.71* | -0.73* |
| /Assets | (0.06) | (0.06) | (0.06) | (0.05) | (0.12) | (0.11) | (0.13) |
| Construction loans | -0.86* | -0.69* | -0.72* | -0.77* | -0.84* | -1.04* | -0.98* |
| /Total loans | (0.10) | (0.10) | (0.10) | (0.08) | (0.17) | (0.16) | (0.18) |
| Liquid assets | -0.68* | -1.78* | -1.58* | -1.07* | -1.36* | -1.09* | 1.20* |
| /Assets | (0.30) | (0.30) | (0.23) | (0.22) | (0.69) | (0.46) | (0.53) |
| Equity | 0.07* | -0.03 | -0.05 | -0.11* | -0.11 | -0.11 | -0.08 |
| /Assets | (0.04) | (0.04) | (0.03) | (0.03) | (0.08) | (0.07) | (0.09) |
| Real estate employment | -0.17* | -0.10* | -0.10* | -0.08* | -0.03* | -0.05* | -0.08* |
| /Total employment | (0.02) | (0.02) | (0.02) | (0.01) | (0.02) | (0.02) | (0.02) |
| Construction employment | -0.34* | -0.28* | -0.27* | -0.22* | -0.07 | -0.13 | -0.28* |
| /Total employment | (0.07) | (0.10) | (0.10) | (0.10) | (0.16) | (0.17) | (0.12) |

Table 16.
Market structure and bank failure probabilities. In the first three columns, each row shows estimated coefficients based on equation (13): $I(ever\ fail)_{i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_{i,t}^{MSA}\Gamma + \varepsilon_{i,t}$, where $I(ever\ fail)_{i,t}^{MSA}$ is an indicator variable set equal to 1 if bank i, observed at time t, eventually fails, and $SHR_{j,i,t}^{MSA}$ is the share of bank i's assets at time t, held in asset class j (asset classes are listed along the column headings). Equation (13) is estimated separately for each year. For the second three columns, each row shows estimated coefficients based on equation (14): $SHR\_EVER\_FAIL_{i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA}\Gamma + \varepsilon_t$. Number of observations for individual bank regressions ranges from 5166 to 3636; for MSA-level regressions number of observations is always 200. Data come from fourth quarter FDIC Call Reports.

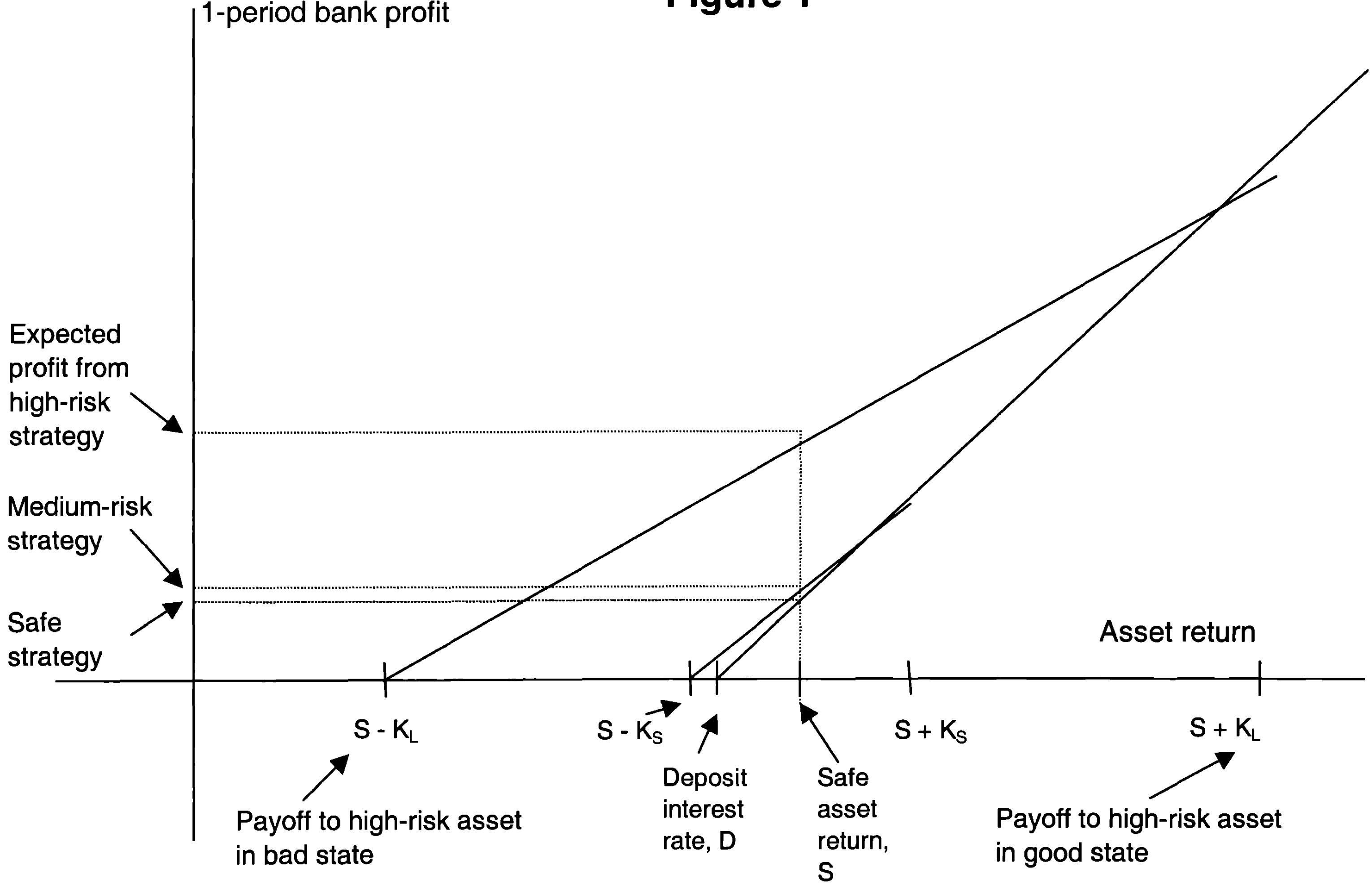
| Sample Controls | Individual banks: None | Individual banks: Region | Individual banks: Region, Bank size, MSA size | Aggregated to MSAs: None | Aggregated to MSAs: Region | Aggregated to MSAs: Region, MSA size | N | Share of banks that eventually fail |
|---|---|---|---|---|---|---|---|---|
| *Year* | | | | | | | | |
| 1980 | -1.64* | -0.97 | -0.86 | -1.47 | -1.95* | -1.92* | 200 MSAs | 8.22% |
| | (0.59) | (0.61) | (0.64) | (0.94) | (0.68) | (0.69) | 5147 banks | |
| 1981 | -1.86* | -1.15 | -1.03 | -1.46 | -1.99* | -1.97* | 200 | 8.56 |
| | (0.61) | (0.63) | (0.65) | (0.96) | (0.71) | (0.72) | (5114) | |
| 1982 | -2.04* | -1.44* | -1.25 | -1.47 | -2.13* | -2.10* | 200 | 9.09 |
| | (0.64) | (0.65) | (0.68) | (0.94) | (0.73) | (0.73) | (5159) | |
| 1983 | -2.09* | -1.19 | -0.79 | -1.61 | -1.80* | -1.78* | 200 | 9.59 |
| | (0.69) | (0.68) | (0.72) | (0.99) | (0.76) | (0.76) | (5015) | |
| 1984 | -4.68* | -2.44* | -2.21* | -2.81* | -2.76* | -2.72* | 200 | 10.27 |
| | (0.71) | (0.70) | (0.75) | (1.01) | (0.78) | (0.79) | (5142) | |
| 1985 | -5.89* | -2.53* | -2.17* | -3.29* | -2.61* | -2.52* | 200 | 10.22 |
| | (0.70) | (0.70) | (0.76) | (0.96) | (0.69) | (0.71) | (5166) | |
| 1986 | -6.05* | -2.41* | -1.89* | -3.15* | -2.47* | -2.33* | 200 | 9.76 |
| | (0.66) | (0.66) | (0.73) | (0.91) | (0.67) | (0.68) | (5156) | |
| 1987 | -3.04* | -1.10 | -0.09 | -2.26* | -1.86* | -1.69* | 200 | 8.90 |
| | (0.67) | (0.64) | (0.70) | (0.97) | (0.69) | (0.70) | (4878) | |
| 1988 | -3.59* | -1.47* | -0.39 | -1.85* | -1.52* | -1.34 | 200 | 7.16 |
| | (0.59) | (0.58) | (0.65) | (0.90) | (0.68) | (0.70) | (4583) | |
| 1989 | -2.00* | -1.16* | -0.23 | -1.29* | -1.25* | -1.02 | 200 | 4.79 |
| | (0.52) | (0.53) | (0.59) | (0.63) | (0.54) | (0.55) | (4422) | |
| 1990 | -0.34 | -0.29 | 0.59 | -0.45 | -0.47 | -0.31 | 200 | 2.98 |
| | (0.43) | (0.44) | (0.51) | (0.53) | (0.50) | (0.50) | (4268) | |
| 1991 | -0.51 | -0.55 | 0.12 | -0.53 | -0.39 | -0.27 | 200 | 2.04 |
| | (0.37) | (0.38) | (0.44) | (0.40) | (0.38) | (0.38) | (4077) | |
| 1992 | 0.62* | -0.15 | 0.38 | 0.15 | 0.14 | 0.23 | 200 | 1.04 |
| | (0.25) | (0.27) | (0.31) | (0.23) | (0.24) | (0.24) | (4145) | |
| 1993 | 0.23 | -0.12 | 0.19 | 0.00 | 0.00 | 0.03 | 200 | 0.49 |
| | (0.18) | (0.19) | (0.23) | (0.19) | (0.19) | (0.19) | (3840) | |
| 1994 | 0.08 | -0.15 | 0.06 | -0.08 | -0.02 | -0.02 | 200 | 0.39 |
| | (0.17) | (0.18) | (0.22) | (0.23) | (0.25) | (0.25) | (3636) | |

Table 17.

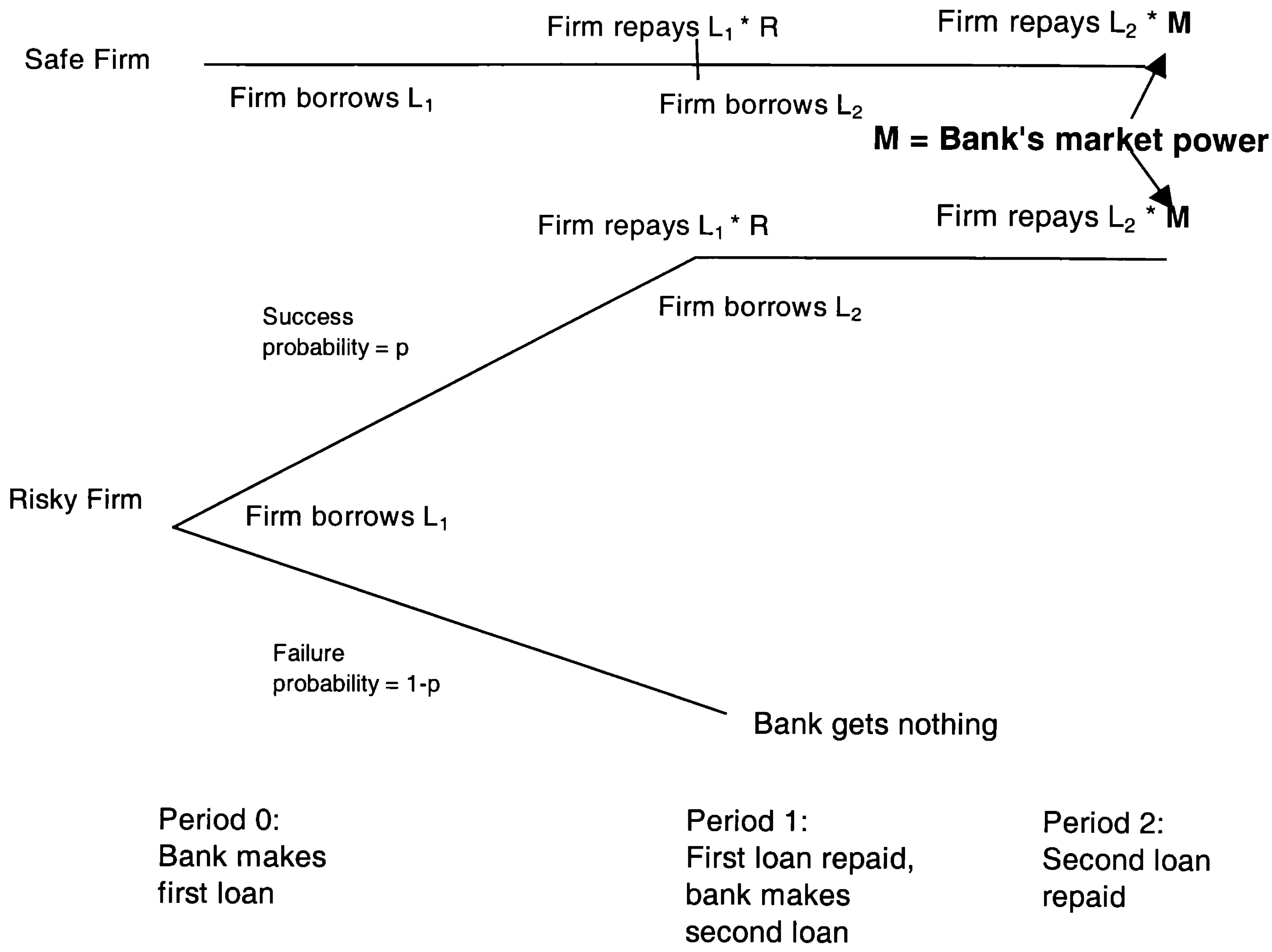
Regressions of failure rates on market concentration. Reported coefficients based on equations (14) through (19) in the text. Controls include bank and MSA size. Equation (14) is a linear probability model regression at the bank level of a dummy for failing on market structure $I(\textit{fail in next year})_{i,t}^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\Gamma + \varepsilon_t^{MSA}$. Equation (15) is a regression at the MSA level of the share of banks failing on market structure: $SHR\_FAIL\_NEXTYEAR_t^{MSA} = \alpha + \beta * HHI_t^{MSA} + X_t^{MSA\prime}\Gamma + \varepsilon_t^{MSA}$. Data come from fourth quarter FDIC Call Reports. Standard errors, reported in parentheses, are corrected for clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Fixed effects | None | None | Year | Region by year | MSA | MSA, year | MSA, Year |
| Controls | None | Yes | Yes | Yes | Yes | Yes | Yes |
| Trends | None | None | None | None | None | None | MSA |
| *Dependent variable* | | | | | | | |
| | | *Unit of observation is the bank-year* | | | | | |
| Bank fails in next year? | -0.29* | -0.30* | -0.34* | -0.10 | 0.07 | -0.06 | -0.37 |
| | (0.05) | (0.06) | (0.06) | (0.06) | (0.15) | (0.15) | (0.26) |
| Bank fails in next 4 years? | -1.63* | -1.75* | -1.59* | -0.46 | -1.84* | -1.33* | -2.97* |
| | (0.21) | (0.24) | (0.24) | (0.24) | (0.42) | (0.42) | (0.55) |
| Bank fails ever? | -2.55* | -2.71* | -2.15* | -0.70 | -2.92* | -1.64* | -2.00* |
| | (0.34) | (0.38) | (0.37) | (0.37) | (0.49) | (0.50) | (0.44) |
| | | *Unit of observation is the MSA-year* | | | | | |
| Share of banks failing next year | -0.20* | -0.19* | -0.20* | -0.16* | -0.22 | -0.31 | -0.35 |
| | (0.06) | (0.07) | (0.07) | (0.06) | (0.18) | (0.18) | (0.26) |
| Share of banks failing in next 4 years | -0.96* | -0.94* | -0.93* | -0.77* | -1.68* | -1.85* | -2.83* |
| | (0.16) | (0.17) | (0.16) | (0.13) | (0.39) | (0.37) | (0.50) |
| Share of banks failing ever | -1.55* | -1.53* | -1.40* | -1.28* | -1.71* | -1.42* | -1.96* |
| | (0.22) | (0.22) | (0.22) | (0.16) | (0.43) | (0.39) | (0.36) |
| Share of assets held at banks failing in next year | -0.26* | -0.27* | -0.29* | -0.23* | 0.04 | -0.08 | -0.12 |
| | (0.09) | (0.09) | (0.09) | (0.08) | (0.24) | (0.24) | (0.35) |
| Share of assets held at banks failing in next 4 years | -1.28* | -1.35* | -1.38* | -1.10* | -0.57 | -0.86 | -2.09* |
| | (0.21) | (0.22) | (0.21) | (0.18) | (0.50) | (0.49) | (0.67) |
| Share of assets held at banks failing ever | -2.17* | -2.33* | -2.20* | -1.95* | -0.32 | -0.03 | -1.45* |
| | (0.29) | (0.29) | (0.29) | (0.23) | (0.54) | (0.51) | (0.43) |

## Figure 1


1-period bank profit
Expected profit from high-risk strategy
Medium-risk strategy
Safe strategy
Asset return
S - $K_L$
S - $K_S$
S + $K_S$
S + $K_L$
Payoff to high-risk asset in bad state
Deposit interest rate, D
Safe asset return, S
Payoff to high-risk asset in good state

## Figure 2


Safe Firm
Firm repays $L_1$ * R
Firm repays $L_2$ * **M**
Firm borrows $L_1$
Firm borrows $L_2$
**M = Bank's market power**
Firm repays $L_1$ * R
Firm repays $L_2$ * **M**
Success probability = p
Firm borrows $L_2$
Risky Firm
Firm borrows $L_1$
Failure probability = 1-p
Bank gets nothing
Period 0: Bank makes first loan
Period 1: First loan repaid, bank makes second loan
Period 2: Second loan repaid

*Chapter 2*
# Banking market concentration and consumer credit constraints: Evidence from the Survey of Consumer Finances

## 2.1. Introduction

Because the timing of income frequently fails to match the desired timing of consumption, credit plays an important role in facilitating the optimal path of consumer spending. The ability to borrow relaxes the constraints on purchases of durable and other goods imposed by the level of financial assets on hand. Reflecting its important position in the American economy, consumer credit outstanding amounted to over 15 percent of GDP in 2000. Over $500 of the $1.57 trillion in credit outstanding was held by commercial banks, with the remainder being securitized or held at finance companies, savings institutions, credit unions, and non-financial companies. This paper assesses the relationship between market concentration in the financial sector and households' perceived levels of credit constraint, and finds evidence that households living in areas where banks enjoy more market power are less likely to have been turned down for credit or discouraged from applying. This paper also finds evidence that interest rates on consumer borrowing decrease much more sharply with age in competitive markets than in more concentrated markets.

These results are consistent with recent models of credit markets, especially those of Petersen and Rajan (1995). Theoretical models of credit provision in which rationing is an equilibrium outcome go back at least to Stiglitz and Weiss (1981); in these models increases interest rates may fail to clear credit markets because of the impact of interest rates on the composition and behavior of borrowers. In particular, as interest rates rise, the pool of borrowers may become riskier and actually reduce the net return to lenders. Petersen and Rajan develop extend these models to explore the relationship between market concentration and lending activity. Their model focuses on the fact that banks are unsure about the likelihood of repayment among new potential borrowers. Banks in concentrated markets, because they will earn monopoly rents on borrowers who eventually prove to be good risks, will have more ex-ante incentive to lend to new borrowers and invest in learning about whether these borrowers are in fact good risks. In the past, this model of competition and credit has been motivated and tested using data on the borrowing practices of small firms. In this paper I present the first evidence on this model using data on consumer borrowing patterns.

It is important to note that this paper uses data from the Federal Reserve Board's 1983 Survey of Consumer Finances (SCF). Financial markets have changed enormously between 1983 and the present date, and removal of barriers restricting entry into banking markets may have attenuated the relationship between the market concentration of a local banking market and the market power enjoyed by the institutions in that market. Nevertheless, the underlying economic forces in this model are certainly still at play: the prices at which 'portfolios' of credit card customers are purchased and sold by financial institutions suggests that whether because of local market concentration or consumer switching costs, banks perceive that something resembling ex-post market power over 'captured' borrowers still exists in this market.

The paper proceeds in four sections. The first section documents the importance of consumer debt in the American economy, focusing both on figures that aggregate consumers and on microeconomic data that allow analysis of the distributions of various types of liabilities. The second section outlines a simple model of banking market concentration, along the lines of Petersen and Rajan, and develops several empirical hypotheses regarding the relationship between market concentration and consumer credit. The third section uses the Federal Reserve Board's Survey of Consumer Finances to test the hypotheses developed in the second section. A brief final section concludes and places the results in context in the rapidly changing American financial market.

### 2.2. Consumer debt in the American economy

This section documents the importance of debt in American household balance sheets. This section's aggregate data on stocks of financial assets come from the Federal Reserve Board's Flow of Funds accounts, and additional aggregate data come from the Federal Reserve's monthly

G19 releases, which contain data on the institutions holding consumer credit. The microeconomic data used throughout this paper come from the Federal Reserve Board's Surveys of Consumer Finances. The SCF, conducted every three years, is an extremely valuable resource for economists working on questions related to household saving and balance sheet behavior. These surveys are uniquely useful because the SCF samples a large number of households and asks enough questions to allow a high degree of disaggregation of assets, liabilities, and income streams.

Table 1, based on data from the Flow of Funds Accounts, documents changes in the aggregate household balance sheet between 1975 and 2000. The numbers in the first panel of Table 1 are in trillions of current dollars, while the second panel of the table presents figures in terms of per-capita 2000 dollars. Turning to the first row of the table, total household liabilities in 1975 amounted to $770 billion, or about 21 percent of financial assets. This amount corresponds to $9500 dollars per capita in 2000 dollars. The bulk of this debt, $460 billion, was secured by residential property. Consumer borrowing in 1975 accounted for $210 billion of household liabilities, or 5.6 percent of financial assets. To put this number into perspective, total household consumption in that year was $1030 billion dollars, $134 billion of which went toward purchases of durable goods.

By 2000, the total borrowing of the household sector amounted to $7.46 trillion, of which $4.92 trillion was secured by home mortgages. Of the remainder, $1.57 trillion was accounted for by consumer loans, or $5700 per person. Comparing the stock of consumer borrowing to flows in the aggregate macroeconomy, this $1.57 trillion in debt was equal to about 15 percent of gross domestic product, and about 23 percent of personal consumption expenditures. The first columns of Table 1 present aggregate asset totals and allow a comparison of debt levels with levels of financial and total assets. As a share of financial assets, consumer liabilities have remained relatively stable over the past twenty-five years. In 1975, these liabilities as a share of financial assets stood at 5.6 percent, and they remained between 5.4 and 5.7 percent from 1975 through 1990. The 1990s have seen rapid growth both in consumer borrowing and in household financial assets, with financial assets pulling slightly ahead: by 2000, aggregate consumer borrowing as a share of financial assets stood at 4.7 percent.

For the financial institutions extending credit, household debt is an asset on their balance sheets. The mix of financial institutions that hold this household debt directly includes commercial banks, savings institutions, credit unions, finance companies, and nonfinancial companies. In addition, a growing share of this debt is pooled and securitized. Table 2 documents changes in the amounts of credit that each of these institutions have held over time. In 1975 and 1980, commercial banks provided more than half of consumer credit, providing $106 billion of the $207 billion outstanding in 1975 and $180 of the $355 outstanding in 1980. In 1985 and 1990, about half of consumer credit was held by commercial banks, but the figure slipped by 2000 to 34 percent with the growing importance of securitization. Finance companies throughout the period have provided about 15 percent of consumer credit, while the share provided by savings institutions rose from five to 10 percent between 1975 and 1985 but has fallen since 1985 to about 4 percent. The share of consumer credit that is pooled and securitized grew rapidly during the 1990s to almost a third.

While Tables 1 and 2 document the aggregate magnitude of consumer borrowing, Table 3 focuses on the distribution across households of different types of debts and assets in the sample from the 1983 Survey of Consumer Finances used for the analysis in this paper. As throughout this paper, this sample includes only the set of households for whom the location of their residence can be established and who reside in metropolitan areas. Section 3, which contains this paper's regression results, discusses in more detail the criteria determining selection into this sample.

The first panel of Table 3 documents household debt and its components in the 1983 cross section. Of the households in the sample, 72.2 percent report having debt, with a mean debt amount of $17,444. Home mortgages, held by 38.5 percent of households, make up $11,010 of this total, or more than half of the aggregate household debt. About 10 percent of households report positive borrowing against lines of credit, and the average amount borrowed in the entire sample is $294. This borrowing against lines of credit is the most highly skewed component of household borrowing, with the mean amount borrowed in the population exceeding the amount borrowed at the 90$^{th}$ percentile.

The bottom rows of the panel show similar statistics for consumer borrowing. 64.1 percent of households report positive consumer borrowing, with the average household having $2916 outstanding. Again, the amounts borrowed are skewed; the median household reported only $500 in borrowing outstanding. Of the $2916 in per-capita borrowing in this sample, outstanding credit card balances, held by 41.6 percent of households accounted for $374. Loans for the purchase of automobiles, held by 29.2 percent of households in the sample, accounted for $1115 per capita, and loans for the purchase of other goods accounted, held by 30.3 percent of households, accounted for $1310.

The bottom panel of table 3 shows total and consumer borrowing relative to income. Scaling these amounts by income provides a sense of the manageability of the debt burdens that households in this sample face. In aggregate, total borrowing as a share of income, including borrowing secured by home mortgages, amounted to 69 percent among the households in the sample. Aggregate consumer borrowing as a share of aggregate income was almost 12 percent, and the distribution of consumer borrowing as a share of income was highly skewed. The median household reports consumer borrowing amounting to 2.6 percent of income, while twenty-five percent of households have consumer borrowing in excess of 13.2 percent of income, and 10 percent surveyed had consumer borrowing in excess of 31.6 percent of income.

Table 4 reports the interest rates that households report paying on their borrowing. Not surprisingly, interest rates on loans that are secured by residential property are low, relative to unsecured loans. This reflects two factors: first, being secured reduces the credit risk (though not the interest rate risk) of mortgage lending. Second, many of these mortgage loans were taken out at fixed rates long before 1983, during periods when interest rates stood at rates far lower than they later attained. Of the 64 percent of households who report positive amounts of consumer borrowing, the mean interest rate paid on all types of consumer borrowing, including credit card balances, auto loans, and non-auto loans, was 14.5 percent. There was substantial variation around this mean, with 25 percent of households reporting interest rates of 11 percent or less, and 25 percent reporting that they were paying interest rates in excess of 18 percent.

Table 5 focuses more tightly on credit cards, reporting aggregate holdings and use of different types of credit cards available. A variety of types of credit cards are available, including cards provided by gas companies; cards provided by banks, such as VISA and Mastercard credit cards; general purpose credit cards such as American Express cards; and credit cards offered by specific retailers. Aggregating all cards together, 69.5 percent of households report holding at least one card, and about 40 percent of households report that they use credit cards for transactions. The most commonly held cards are bank credit cards, held by 47 percent of the sample, and credit cards offered by national retailers, held by 52 percent of the sample. Less common in 1983 were general purpose credit cards and gas company cards.

The data documented in this section point to the significance of consumer credit in the American economy. At the aggregate level, this type of borrowing amounts to about 15 percent of GDP. In addition, for a sizable share of households, this type of borrowing exceeds current income by substantial amounts. This points to the importance of consumer credit in smoothing consumption across income shocks and to meet the desired pattern of spending.

### 2.3. Banking market concentration and consumer lending: theory

Theoretical models outlining how credit rationing can be a feature of equilibrium in financial markets go back at least to the work of Stiglitz and Weiss (1981). The intuition behind these models is that lenders can neither perfectly evaluate nor perfectly monitor potential borrowers, leaving banks uncertain about whether an individual borrower will repay a particular loan. Increasing interest rates can affect both the pool of borrowers applying for credit and how they behave once they are extended credit, possibly in ways that substantially reduce the likelihood of repayment. In such a model, by raising interest rates, banks may find their net return on lending falling because of a decline in the odds that loans are repaid. With the price of credit no longer able to equilibrate supply and demand, credit rationing can become a part of equilibrium in financial markets.

A recent line of research by Petersen and Rajan (1995) explores the impact of credit market competition on the credit constraints of potential borrowers, and it is this model that inspires the empirical work in that follows. The intuition is that banks are again uncertain about the potential quality of borrowers, but the innovation in this model is that banks will have the opportunity to make additional loans to borrowers after the initial loan, having observed the borrower's performance in repaying the first loan. When making a loan to a new borrower, Stiglitz-Weiss type effects may limit the ability to raise the interest rate. In subsequent periods, having observed borrowers' repayment performance, the balance of information is tilted toward the bank, and their ability to raise interest rates is limited more by monopoly power than by information problems. On these subsequent loans to borrowers, banks with market power will earn ex-post rents that allow an intertemporal cross-subsidization; monopolist banks can make negative NPV loans to young borrowers firms if those who prove to be good risks will continue to purchase credit from the bank at interest rates that are kept high by market power. Because competition among banks reduces their ability to extract these ex-post rents, as markets become less concentrated credit constraints on new borrowers may bind more tightly.

This model motivates the two empirical tests in the sections that follow. The first set of tests look at the relationship between banking market structure at the metropolitan level and the probability that households are credit constrained, focusing in particular on younger borrowers. The second set of tests examines the relationship between borrower age and the interest rate paid on consumer borrowing across different competitiveness regimes. In more competitive markets, loans must be breakeven propositions in each period, preventing the type of intertemporal cross-subsidization that is at the heart of the Petersen-Rajan model.

It is important to note that the empirical work that follows is based on data from 1983 and on a model where banking markets are defined at the local metropolitan area level. It is beyond doubt that banking markets have changed enormously in the period since 1983; states have opened their markets to competition from both within-state and outside competitors. In addition, as Table 2 documented, the relative importance of depository institutions in these markets has fallen over time. But the underlying economic forces at work in this model are undoubtedly potentially still at play, albeit in different forms. If consumers vary for any reason in their reluctance to 'switch' credit providers, and this variation is correlated with observable factors, then everything in the model above still goes through, with 'apparent reluctance to switch, once captured' substituted for 'local market-concentration-derived market power.'

It is also important to note that the Petersen-Rajan model, primarily a model of business credit, has not been applied to consumer credit markets. Because consumer credit markets differ along a variety of dimensions from commercial credit markets, it is open to debate whether such a model should apply to the consumer side, and the empirical analysis that follows is an attempt to assess this very question

### 2.4. Empirical approach and results

The analysis that follows uses data from the 1983 Survey of Consumer Finances. As mentioned in the first section, the Surveys of Consumer Finances are conducted every 3 years by the Federal Reserve Board, and the 1983 Survey sampled 4262 households and asked a range of questions about household characteristics, income, and asset and liability totals. Most importantly, this was the last Survey for which information about the respondent's MSA of residence is publicly available. More recent Surveys do not include this information because of concerns about maintaining confidentiality for the households that respond to the Survey. Knowing a household's MSA allows me to link these data with data that describe banking market concentration at the MSA level, as well with data that describe the banking regulation and political environment at the state level.

Of the 4262 households surveyed by the 1983 Survey, 438 were part of a high-income oversample group designed to get a detailed picture at the asset holdings of the very wealthiest households. Even in 1983, because of confidentiality concerns, the MSAs of these households are not revealed on the public-use SCF dataset. The remainder came from an area sample, and of these households 2553 are in 59 MSAs and can be linked to data on banking market structure at the local level. Table 6 presents summary statistics for the variables used in the analysis that follows. The first row presents the distribution of the variable used to measure credit constraint. It is based on the responses to two survey questions; the first question asks whether the respondent has been turned down for credit in the past few years, or has not been given as much credit as requested. The precise wording of the first question is given below:

> TURNED DOWN FOR CREDIT IN LAST FEW YEARS?
> Respondents were asked if he/she (or their spouse) had had a request for credit turned down by a particular lender or creditor in the past few years, or had been unable to get as much credit as he/she had applied for.
> 1. yes, turned down
> 3. yes, unable to get as much credit as he/she wanted
> 5. not turned down

Households that either report being turned down for credit or report being unable to get as much credit as requested are considered credit constrained. The second question asks whether they have been dissuaded from applying for credit, meaning that they had thought about applying for credit at a particular place but changed their mind because they thought they might be turned down. Again, the text of the question is outlined below:

> DISSUADED FROM APPLYING FOR CREDIT?
> Respondents were asked if there had been any time in the past few years that he/she (or their spouse) had thought about

applying for credit at a particular place, but changed their mind because he/she thought he/she might be turned down.

1. yes
5. no

In almost all of the analysis that follows, households are considered to consider themselves credit constrained if they answer yes to either of the questions documented above. It is important to have both questions, because without the second question, changes in the share of households whose credit requests are turned down could reflect either true changes in credit constraint or changes in the share of households applying for credit, making the results more ambiguous than when the 'discouraged from applying' question is included as well. By the measure that includes both rejection and discouragement, I find that 23.3 percent of households in the sample report being credit constrained.

Column 2 documents the range in income in the sample. The mean in the sample is \$25266, and the range between the $10^{th}$ and $90^{th}$ percentiles is \$5712 to \$50000, and the median is \$21000. For net worth, the mean is \$78605, and the median is \$34025. The range between the $10^{th}$ and $90^{th}$ percentiles is \$150 to \$180658, reflecting the great variation in wealth that characterizes the distribution. The mean age of household head is 45.4 years, and the median is 42. As noted earlier, households report paying a range of interest rates on their consumer and credit card debt. The mean rate paid is 14.4 percent, and the median is 16.1 percent. The range from the $25^{th}$ to the $75^{th}$ percentile is 10.9 to 18.3 percent.

This paper uses a measure of banking market concentration known as the Herfindahl Index. This index is 10000 times the sum of squared market shares of the banks in each MSA, computed on the basis of deposits. A completely monopolized market would have a Herfindahl Index of 10000, while a market with 5 equal-size banks would have a Herfindahl Index of 2000. The SCF respondents live in 59 MSAs, and the mean Herfindahl index across these MSAs is

1643. The median is 1561, and the range between 25th and 75th percentiles is 1013 to 2003. Reflecting the fact that more populous MSAs tend to have somewhat lower Herfindahl Indexes, these numbers are lower when weighted by household than when weighted by MSA. The subsections that follow use these data to assess the relationship between market concentration and consumer credit constraint.

Table 7 describes in more detail the variation in concentration and in the share reporting credit constraint across the 59 MSAs represented in the Surveys of Consumer Finances. One thing that stands out is the variation across these MSAs, both in the Herfindahl Index and in the share reporting discouragement. While the Herfindahl indexes are presumably precisely estimated, the small sample size within each MSA means that many of the discouragement numbers are measured somewhat less precisely. Thus, the fourth column of the table shows the standard error of the estimated mean reported in the third column.

**2.4.1. Concentration and unsatisfied borrowers**

The first regressions estimate the relationship between market concentration and the share of borrowers reporting that they have had credit requests turned down or discouraged. Equation (5) below shows the basic form of these regressions:

(5) $\mathrm{I}(\textit{constrained})_i = \alpha + \beta * \mathrm{HHI}_i^{\mathrm{MSA}} + X_i\beta + \varepsilon_i$

The first column of Table 5 reports the coefficient from the model estimated with no control variables of any kind. In this most simple reduced form, there appears to be some correlation between concentration and the share of borrowers reporting being constrained, although the relationship is statistically significant only at the 10 percent level. In this sample, an increase of 500 Herfindahl points is associated in this sample with an increase of 9.5 percent in the share of borrowers reporting that they are credit constrained in either of the two ways mentioned earlier.

The second and third columns of Table 8 include linear controls for household age, income, and net worth. The second column applies linear controls for these factors, and the third column uses dummy variables that allow a nonlinear relationship between income and net worth and the dependent variable. In each of these specifications, the impact of banking market concentration on the share reporting credit constraint is negative, meaning that fewer borrowers in concentrated markets are reporting being unable to borrow. Not surprisingly, in this sample increases in both household income and wealth are associated with reductions in reports of credit constraint. Households with incomes above $50000 were about 12 percent less likely to report constraint than households with incomes below $20000, and households reporting net worth in excess of $100000 were 20 percent less likely to report credit constraint than households reporting negative net worth.

A possible problem with the empirical analysis in columns (1) through (3) is that concentration and household reports of credit constraint may be correlated for reasons other than a causal effect of concentration on borrowing constraints. Concern is alleviated a bit, however, by the fact that my analysis links concentration from a survey of banks to constraints from a survey of households and thus removes any mechanical connections between the two variables. If, however, there is variation across the business cycle in concentration, one might find a spurious correlation between credit constraint and concentration, one that does not reflect any causal impact of one on the other. Controlling for household income and local macroeconomic conditions is one approach to dealing with this problem, and the results below are strikingly robust to this control function approach. An additional approach to identifying the causal relationship is to use instrumental variables (IV) techniques. These techniques regress the credit constraint variable on concentration using only the part of the statistical variation in concentration that is correlated with a set of third variables, called instrumental variables. The idea is to purge the variation in concentration of components that might be spuriously correlated with credit constraint. The identifying assumption is that variation in these instrumental variables only affects borrowing activity through their impact on concentration.

The instruments used in table 8 include a set of dummy variables for the political environment in the state in 1983. The motivating assumption is that the major political parties in the United States are differentially hostile to deregulation and market power on the part of banks. As such, we use 5 instruments: dummy variables for whether the governorship and two houses of congress are controlled by Democrats, a dummy variable for uniform Democrat control of the three branches of government, and a dummy variable for uniform Republican control.

Columns (4) through (6) document the results of this empirical exercise. They show that the variation in Herfindahl Index that can be described by these political variables is much more strongly associated with credit constraints than the other variation. The results are consistent with the intuition that market power and credit constraints are linked. The estimated magnitude of these coefficients is fairly large, perhaps large enough to be implausible that it holds throughout the distribution. According to the coefficient estimate in column (6), a 250 basis point increase in concentration is associated with a 12.7 percentage point drop in the share of consumers reporting credit constraint.

As noted earlier, the results in Table 8 are based on a dependent variable that aggregated households responses to two questions: one question for whether the household had had a credit request turned down, and another for whether the household had avoided applying for credit because they thought they might get turned down. Table 9 presents results based on the responses to these two questions separately. Focusing on columns (3) and (6), which contain a rich set of controls for income and for net worth, the magnitude of the effect of market concentration on being turned down for credit ('TURN DOWN') is precisely the same as the magnitude of the effect on not asking for credit in the first place ('DON'T ASK'.) The impact on 'TURN DOWN' is statistically significant at the 10 percent level but not the 5 percent level, while the impact on the 'DON'T ASK' variable is statistically significant at the 5 percent level. Focusing on the control variables in columns (3) and (6), the marginal impact of age on each measure of credit constraint is roughly similar. The same is true for net worth; wealthy households are roughly 15 percent less likely to report not having requested credit and 15 percent less likely to report having a credit request denied. With respect to income, there is evidence that low-income households are much more likely to report having avoided requesting credit for fear of being turned down. The marginal impact of income on actually being turned down, however, in a regression that controls for net worth and other variables, is not significant.

Other government policies may affect the share of consumers having trouble borrowing. Foremost among these, as emphasized in a recent paper by Gropp, Scholz, and White (1997), are state policies toward borrowers who declare bankruptcy. There is important variation across states in the amount of assets that bankrupt borrowers are allowed to shield from their creditors. In many states, consumers who declare bankruptcy are able to shield substantial assets from creditors. States like Texas are particularly generous, protecting the entire value of borrowers' homes from creditors in the event of bankruptcy. Other states, such as Iowa, have policies that are much less generous toward borrowers who declare bankruptcy. Because these differences in state bankruptcy exemptions affect the return to bank lending, they may also affect the share of consumers who find that they are unable to get credit. The rest of the results presented in this paper control for these cross-state differences in bankruptcy exemption.

Table 10 controls for bankruptcy exemptions using data from Gropp, Scholz, and White (1997) to construct dummy variables based exemption generosity. States have different exemption limits for residential assets and other types of assets; the dummy variables are constructed by aggregating these limits to form a total bankruptcy exemption limit. The results in this table are even stronger than in the previous tables, suggesting that concentration-constraint relationship is robust to controlling for this other element of policy. Looking in particular at columns (3) and (6) of Table 10, both OLS and IV models suggest that an increase of 250 Herfindahl Indexes is associated with a reduction in the share reporting credit constraints of between 7 and 12 percentage points. Focusing on the coefficients on the bankruptcy exemption dummy variables, there is evidence that borrowers living in states with more bankruptcy law that is more generous toward defaulting borrowers are more likely to report that they are credit constrained. Households residing in states where defaulting borrowers are allowed to shield more than \$25000 from creditors are between 5 and 9 percent more likely to report credit constraint than households living in less generous states. By way of comparison, in this sample a 1000 point increase in a locale banking market Herfindahl Index is associated with a roughly 3.5 percent reduction in households' probability of reporting credit constraints.

Another concern about the results documented in Tables 8 through 10 would be that the correlation between credit constraints and MSA banking market concentration reflects some joint correlation with MSA size or with local urbanization levels rather than a causal effect of concentration on credit constraints. Table 11 controls for locale-specific effects with dummy variables for different types of locations and with variables capturing the size of the metropolitan area in which the household resides. The regression documented in column (2), in particular, contains 5 dummy variables to the respondent's 'locale': one for respondents living in the central cities of the 10 major metropolitan areas, another for respondents residing in other MSAs, dummy variables for respondents in living the suburbs of large and small MSAs, and an additional dummy for respondents living in parts of MSAs that are not suburban but still within 50 miles of the MSA center. The excluded dummy variable is for a small number of households living within MSAs but more than 50 miles from the MSA center. These households reside almost exclusively in the western part of the United States, where such a location is possible. The regression reported in column (2) also controls for the natural logarithm of MSA size. Together, these controls account in a very rich way for the size and the level of urbanization of the respondent's locale. Adding these controls, the coefficient on the MSA Herfindahl Index is negative and statistically significant at the 5 percent level. Focusing on the added control variables, there is evidence that households living in larger metropolitan areas, and households living in the central cities of metropolitan areas, are more likely to report that they are credit constrained.

The magnitude of the results in Table 8 and Table 10 seems large, and these large coefficients may perhaps not accurately reflect the slope of the relationship throughout the distribution of concentration. The Justice Department uses a Herfindahl Index of 1800 to separate moderately from highly concentrated markets, and scrutiny of mergers depends largely on whether the local market Herfindahl index exceeds this figure. Table 12 performs the same analysis as table 10, using a dummy variable for MSAs where the Herfindahl Index exceeds 1800. These equations fit variations of the following model:

(6) $\quad I(\textit{constrained})_i = \alpha + \beta * I(HHI_i^{MSA} \geq 1800) + X_i\beta + \varepsilon_i$

I(X) represents an indicator function, set equal to 1 if the expression X is true. The results in Table 7 are consistent with a strong impact of concentration on credit constraint. Taking the estimate in column (3), households in markets which are highly concentrated are 5 percent less likely to report credit constraint; the IV results suggest that households in highly concentrated markets are as much as 23 percent less likely to report constraints. The magnitude of this effect appears to be approximately same order of magnitude as the impact of generous state bankruptcy exemptions.

Tables 13 performs the same analysis as Table 10, with an expanded set of control variables, including education, race, and region dummy variables. All regressions in these tables include the full set of dummy variables for state bankruptcy exemptions, household income, household net worth, as well as a linear term for the age of the household head. These results are broadly consistent with the earlier results. Only in the IV regression which includes dummy variables for region is the impact of concentration on constraint not statistically significant. In column (6) of Table 9, the estimated coefficient of 7.47, with a standard error of 4.74, is not different from 0 using standard measures of statistical confidence, a fact that may reflect the collinearity between region and the political control variables. All of the regressions show strong evidence that black households are more likely to report credit constraints. The largest point estimate among the race coefficients is for American Indians; the point estimate of 0.24 with a standard error of 0.13, while suggestive, is statistically significant at the 10 percent level but not at the five percent level. There is weak evidence that, controlling for other household characteristics, households with some college are more likely to report being credit constrained.

There is also evidence, statistically significant at the 10 percent level, that households living in the North Central states are less likely than households in the East to report being credit constrained.

Table 14 looks separately at the marginal impact of market concentration among younger borrowers (households where the household head is younger than 40 years old) and older borrowers (households where the head is 40 and older.) The results documented in this table provides some evidence that the marginal impact of market concentration is larger among younger households. In the OLS estimates in columns (1) and (4), the difference between the coefficients on young and old borrowers is large both in the statistical sense and in the economic sense. However, for the IV results in columns (2),(3),(5), and (6), the differences are not as large. Among the other control variables, the most striking difference between older and younger borrowers is among households reporting Native American ethnicity; the coefficient on these households among the young cohorts is a whopping 60 percentage points, while among the older households the coefficient on the Native American dummy variable represents a negative 15 percentage point marginal effect.

All of the results documented so far have used the Herfindahl-Hirschman Index, constructed using commercial bank deposits, as a measure of local banking market concentration. Table 15 broadens the analysis by presenting results corresponding to different measures of financial market concentration. Column (1) uses the Herfindahl Index of the commercial banks in the MSA. Column (2) uses a dummy variable for MSAs whose commercial bank HHI exceeds 1800. Column (3) reports results using a Herfindahl Index, this time constructed for all depository instutitions rather than just commercial banks. Most importantly, this measure of concentration includes depository institutions in the savings and loan industry, an important sector in many areas of the country. Columns (4) and (5) use 3-firm concentration ratios, which measure the share of deposits in the market held at the three largest institutions. Column (4) uses a concentration ratio constructed on commercial banks, and column (5) is based on all depository institutions.

Across all of these results measures of market concentration, there is a statistically and economically significant effect on the share of households reporting credit constraint. The marginal impact of the commercial banking industry Herfindahl Index, as estimated earlier, is –3.47 percentage points per 1000 point index change. Using a dummy variable for MSAs with commercial banking Herfindahl Indexes in excess of 1800 gives a marginal effect of –5.20 percentage points. Using the Herfindahl measure of concentration based on the entire set of depository institutions gives a coefficient of –4.56, larger in magnitude than the measure based only on the commercial banking industry. The final two columns of Table 15 use concentration ratios. Results based both on the commercial banking sector and on the entire set of depository institutions suggest that a 10 percentage point increase in the share of assets held at the 3 largest institutions is associated with approximately a 2 percentage point reduction in the probability that a household reports being credit constrained.

**2.4.2. Lending interest rates and borrower age across different competitiveness regimes**

Cross-subsidization between new and existing borrowers is key to the Petersen-Rajan model: a monopolist can recoup losses on loans to new borrowers through higher interest rates on subsequent loans to borrowers who turn out to be good risks. Table 11 tests an implication of this cross-subsidization: that the slope of interest rates on consumer loans should be steeper in more competitive markets than in concentrated markets.

Table 11 presents evidence supportive of the cross-subsidization hypothesis. Equation (7) below is the empirical model fit in these equations:

(7) $\quad INTRATE_i^{MSA} = \alpha + \beta * AGE_i^{MSA} + X_i\Gamma + \varepsilon_i$ ,

This model is fit separately on a sample of concentrated MSAs (with Herfindahl indexes above 1800) and a sample of less concentrated MSAs (Herfindahl indexes below 1800). In the more concentrated sample, the coefficient on the age variable is –0.31 (standard error 0.26), meaning that as age rises by 10 years, the reported interest rate on consumer borrowing falls by 30 basis points. In less concentrated markets, reported interest rates decline much more steeply with age. In equation (6), which controls for the full set of demographic control variables, the coefficient of –0.64 (0.18) implies that a 10 year increase in age is associated with a 64 basis point drop in the interest rate on consumer borrowing. The difference between these estimated coefficients is statistically significant; nesting the equations in the same model along the lines of equation (8)

$$(8) \qquad INTRATE_i^{MSA} = \alpha + \beta * AGE_i^{MSA} + \gamma * AGE_i^{MSA} * I(HHI_i^{MSA} \geq 1800) + X_i\beta + \varepsilon_i$$

the coefficient $\gamma$ is positive and significant at the 5 percent confidence level.

**2.5. Conclusion**

This paper presents the first evidence on the relationship between market concentration in the banking sector and household reports of credit constraints. There is substantial evidence both that more concentrated banking markets have fewer constrained borrowers and for the type of cross-subsidization across borrowers that is the key to theoretical models of concentration and credit constraint. The magnitude of these effects is large: moving from concentrated to competitive banking market regimes in 1983 is associated with a change in credit constraint similar to moving from a state where assets are unprotected in bankruptcy to a state offering substantial opportunities to shield assets from creditors.

American financial markets have changed substantially over the 18 years since the data used in this paper were collected. Many of these changes may have affected the relationship between banking market concentration and credit constraints, especially at the local level. In particular, banking markets may have become increasingly regional and national, as the relaxation of branching restrictions has enabled bank holding companies to expand and compete across a number of local markets. Perhaps most important, the proliferation of information technology and information about borrowers allows lenders to assess credit-worthiness of potential borrowers from afar almost as effectively as local banks can. Whether there is still a relationship between concentration and credit constraints is still an open empirical question.

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Table 1.
Aggregate household sector balance sheets, 1975-2000. Data from Federal Reserve Flow of Funds Z1 releases.

| | Assets | | | Liabilities | | | |
|---|---|---|---|---|---|---|---|
| Year | Financial | Tangible | Total | Consumer | Mortgage | Total | Net Worth |
| *Trillions of current dollars* | | | | | | | |
| 1975 | $3.73 Tr | $2.25 | $5.98 | $0.21 | $0.46 | $0.77 | $5.22 |
| 1980 | 6.64 | 4.38 | 11.02 | 0.36 | 0.93 | 1.46 | 9.57 |
| 1985 | 10.04 | 6.57 | 16.61 | 0.60 | 1.46 | 2.38 | 14.23 |
| 1990 | 14.85 | 9.33 | 24.17 | 0.81 | 2.53 | 3.75 | 20.43 |
| 1995 | 21.64 | 10.70 | 32.33 | 1.12 | 3.38 | 5.11 | 27.22 |
| 2000 | 33.14 | 15.28 | 48.42 | 1.57 | 4.92 | 7.46 | 40.96 |
| *Per-capita 2000 dollars* | | | | | | | |
| 1975 | $46.0 k | $27.7 | $73.8 | $2.6 | $5.7 | $9.5 | $64.4 |
| 1980 | 54.6 | 36.0 | 90.6 | 3.0 | 7.6 | 12.0 | 78.7 |
| 1985 | 61.0 | 39.9 | 101.0 | 3.6 | 8.9 | 14.5 | 86.5 |
| 1990 | 73.3 | 46.1 | 119.3 | 4.0 | 12.5 | 18.5 | 100.9 |
| 1995 | 89.5 | 44.2 | 133.7 | 4.6 | 14.0 | 21.1 | 112.5 |
| 2000 | 119.9 | 55.3 | 175.2 | 5.7 | 17.8 | 27.0 | 148.2 |

Table 2.
Holders of consumer credit, December 1975-December 2000. Data from Federal Reserve Board G19 releases. All figures in billions of current dollars.

| | | Consumer credit held by | | | | | |
|---|---|---|---|---|---|---|---|
| Year | Total consumer credit | Commercial banks | Finance companies | Credit unions | Savings institutions | Nonfinancial business | Pools of securitized assets |
| 1975 | $207 | $106 | $33 | $26 | $10 | $33 | $0 |
| 1980 | 355 | 180 | 62 | 44 | 23 | 46 | 0 |
| 1985 | 603 | 297 | 117 | 74 | 58 | 63 | 0 |
| 1990 | 805 | 382 | 133 | 92 | 50 | 72 | 77 |
| 1995 | 1123 | 502 | 152 | 132 | 40 | 85 | 212 |
| 2000 | 1593 | 541 | 220 | 184 | 65 | 83 | 500 |

Table 3.
Summary statistics for balance sheet variables, 1983 SCF. Data from 1983 Federal Reserve Survey of Consumer Finances. All figures in 1983 dollars. For ratio figures, figure listed as mean is the ratio of the means. Percentiles listed are the percentiles of the distribution.

| | | | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | Share > 0 | Mean | Std. Dev. | 10th | 25th | 50th | 75th | 90th |
| *Debt Levels:* | | | | | | | | |
| Total debt | 72.2% | \$17444 | \$40901 | \$0 | \$0 | \$3296 | \$23636 | \$49811 |
| Real estate debt | | | | | | | | |
| Home mortgages | 38.5 | 11010 | 19926 | 0 | 0 | 0 | 15297 | 39139 |
| Other real estate mortgages | 7.8 | 3095 | 31377 | 0 | 0 | 0 | 0 | 0 |
| Land contracts | 0.9 | 247 | 3670 | 0 | 0 | 0 | 0 | 0 |
| Lines of credit | | | | | | | | |
| Secured with residence | 0.3 | 44 | 1497 | 0 | 0 | 0 | 0 | 0 |
| Not secured with residence | 11.3 | 250 | 2043 | 0 | 0 | 0 | 0 | 200 |
| Consumer borrowing | | | | | | | | |
| Total | 64.1 | 2916 | 6409 | 0 | 0 | 500 | 3400 | 8247 |
| Credit card | 41.6 | 374 | 828 | 0 | 0 | 0 | 390 | 1200 |
| Closed-end consumer debt | 49.0 | 2542 | 6230 | 0 | 0 | 0 | 2831 | 7180 |
| Auto | 29.2 | 1115 | 2487 | 0 | 0 | 0 | 753 | 4367 |
| Non-auto | 30.3 | 1310 | 5332 | 0 | 0 | 0 | 302 | 2947 |
| *Income, asset and net worth levels:* | | | | | | | | |
| Income | 100.0 | 25266 | 19922 | 5712 | 11303 | 21000 | 34050 | 50000 |
| Financial Assets | 88.9 | 17072 | 58866 | 0 | 345 | 2500 | 12665 | 41700 |
| Net Worth | 91.2 | 78605 | 196872 | 150 | 4225 | 34025 | 89550 | 180658 |
| *Ratios:* | | | | | | | | |
| Total borrowing to income | 72.2% | 69.0% | - | 0% | 0% | 16.8% | 84.2% | 166.1% |
| Consumer borrowing to income | 64.1 | 11.5 | - | 0 | 0 | 2.6 | 13.5 | 31.2 |

Table 4.
Summary statistics for interest rates paid on debt, 1983 SCF. Data from 1983 Federal Reserve Survey of Consumer Finances. All figures are percentages.

| | | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | 10th | 25th | 50th | 75th | 90th |
| Home mortgages | 9.5% | 2.9% | 6.0% | 7.7% | 9.0% | 11.0% | 13.2% |
| Other real estate mortgages | 10.4 | 3.1 | 7.0 | 8.6 | 10.0 | 12.0 | 14.5 |
| Consumer borrowing: | 14.5 | 6.8 | 4.7 | 10.9 | 16.6 | 18.3 | 21.0 |
| Credit card | 15.0 | 7.6 | 0.0 | 15.0 | 18.0 | 18.0 | 21.0 |
| Closed-end consumer debt: | 14.6 | 6.4 | 5.6 | 10.7 | 15.5 | 18.6 | 21.9 |
| Auto | 16.7 | 5.4 | 10.5 | 14.3 | 16.8 | 18.9 | 23.4 |
| Non-auto | 12.9 | 7.2 | 2.0 | 7.0 | 13.6 | 18.5 | 22.2 |

Table 5.
Summary statistics for credit card use, 1983 SCF. Data from 1983 Federal Reserve Survey of Consumer Finances. All figures are percentages.

| | All cards | Gas company cards | Bank credit cards | General purpose credit cards | National retailer credit cards | Other retailer credit cards | Other credit cards |
|---|---|---|---|---|---|---|---|
| *Number of cards held* | | | | | | | |
| 0 | 30.5% | 69.7% | 52.7% | 88.8 | 47.9 | 56.4 | 94.4 |
| 1 | 9.9 | 12.7 | 28.8 | 9.6 | 24.7 | 15.7 | 4.4 |
| 2 | 10.1 | 7.4 | 14.8 | 1.3 | 17.2 | 11.3 | 0.9 |
| 3 | 7.1 | 5.1 | 2.6 | 0.4 | 8.9 | 7.4 | 0.3 |
| >3 | 41.8 | 5.2 | 1.2 | 0.0 | 1.4 | 9.2 | 0.1 |
| *Frequency of use* | | | | | | | |
| No card | 30.5% | 69.7% | 52.7% | 88.8% | 47.9% | 56.4% | 94.4% |
| Never, but have card | 29.7 | 12.7 | 13.8 | 3.6 | 6.0 | 6.6 | 0.4 |
| Hardly ever | 24.2 | 5.8 | 19.1 | 4.0 | 20.9 | 18.2 | 1.0 |
| Sometimes | 13.8 | 9.3 | 12.7 | 3.2 | 21.9 | 15.8 | 2.5 |
| Often | 1.8 | 2.4 | 1.8 | 0.4 | 3.4 | 3.0 | 1.8 |

Table 6.
Summary statistics. Data based on sample from 1983 Federal Reserve Board Survey of Consumer Finances. Banking market concentration from Philip Strahan, political variables from 1984 U.S. Statistical Abstract.

| | | | | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Unit | Obs. | Mean | S.D. | $10^{th}$ | $25^{th}$ | $50^{th}$ | $75^{th}$ | $90^{th}$ |
| *SCF variables:* | | | | | | | | | |
| Credit denied or discouraged | HH | 2553 | 0.233 | 0.423 | 0 | 0 | 0 | 0 | 1 |
| Income | HH | 2553 | \$25266 | 19922 | 5712 | 11303 | 21000 | 34050 | 50000 |
| Net Worth | HH | 2553 | \$78605 | 196872 | 150 | 4225 | 34025 | 89550 | 180658 |
| Head age | HH | 2553 | 45.4 | 16.9 | 25 | 31 | 42 | 59 | 70 |
| Interest rate on consumer debt | HH | | 14.5% | 6.8 | 4.7 | 10.9 | 16.6 | 18.3 | 21.0 |
| *Banking market concentration variables:* | | | | | | | | | |
| Herfindahl Index | HH | 2553 | 1586 | 846 | 562 | 991 | 1468 | 1935 | 2729 |
| Herfindahl Index | MSA | 59 | 1643 | 841 | 633 | 1013 | 1561 | 2003 | 2794 |
| *Political control variables:* | | | | | | | | | |
| Democrats control: | | | | | | | | | |
| Governor | MSA | 59 | 0.559 | 0.501 | 0 | 0 | 1 | 1 | 1 |
| Senate | MSA | 59 | 0.814 | 0.393 | 0 | 1 | 1 | 1 | 1 |
| House | MSA | 59 | 0.915 | 0.281 | 1 | 1 | 1 | 1 | 1 |
| All branches | MSA | 59 | 0.475 | 0.504 | 0 | 0 | 0 | 1 | 1 |
| Republicans control: | | | | | | | | | |
| All branches | MSA | 59 | 0.051 | 0.222 | 0 | 0 | 0 | 0 | 0 |

Table 7.
Market concentration and credit discouragement, across MSAs. Data from 1983 SCF.

| MSA code | MSA name | HHI | Share reporting credit denied or discouraged | Standard error of estimate | N |
|---|---|---|---|---|---|
| 40 | Abilene | 2397 | 0.357 | 0.092 | 28 |
| 360 | Anaheim-Santa Ana-Garden Grove | 1013 | 0.304 | 0.098 | 25 |
| 520 | Atlanta | 1408 | 0.246 | 0.058 | 57 |
| 620 | Aurora-Elgin | 561 | 0.200 | 0.092 | 21 |
| 720 | Baltimore | 1544 | 0.242 | 0.076 | 35 |
| 860 | Bellingham | 1690 | 0.245 | 0.062 | 49 |
| 1120 | Boston | 1259 | 0.190 | 0.061 | 43 |
| 1140 | Bradenton | 1683 | 0.286 | 0.087 | 30 |
| 1160 | Bridgeport | 2194 | 0.182 | 0.068 | 34 |
| 1480 | Charleston | 1031 | 0.070 | 0.039 | 45 |
| 1600 | Chicago | 893 | 0.221 | 0.051 | 74 |
| 1680 | Cleveland-Lorain-Elyria | 1808 | 0.105 | 0.050 | 40 |
| 1760 | Columbia | 1561 | 0.244 | 0.049 | 79 |
| 2000 | Dayton-Springfield | 1451 | 0.188 | 0.070 | 35 |
| 2160 | Detroit | 1312 | 0.300 | 0.052 | 83 |
| 2285 | East St. Louis-Belleville | 633 | 0.300 | 0.153 | 10 |
| 2400 | Eugene-Springfield | 2150 | 0.169 | 0.045 | 72 |
| 2640 | Flint | 3060 | 0.269 | 0.062 | 52 |
| 2960 | Gary | 1024 | 0.214 | 0.114 | 15 |
| 3200 | Hamilton-Middletown | 3187 | 0.161 | 0.067 | 33 |
| 3360 | Houston | 991 | 0.389 | 0.058 | 83 |
| 3480 | Indianapolis | 1729 | 0.154 | 0.059 | 39 |
| 3640 | Jersey City | 1810 | 0.200 | 0.133 | 10 |
| 3965 | Lake County | 525 | 0.048 | 0.048 | 23 |
| 4400 | Little Rock-North Little Rock | 1083 | 0.323 | 0.060 | 62 |
| 4480 | Los Angeles-Long Beach | 1395 | 0.337 | 0.047 | 108 |
| 4520 | Louisville | 1905 | 0.163 | 0.057 | 49 |
| 5000 | Miami | 809 | 0.261 | 0.094 | 24 |
| 5015 | Middlesex-Somerset-Hunterdon | 555 | 0.175 | 0.048 | 64 |
| 5120 | Minneapolis-St. Paul | 2003 | 0.169 | 0.049 | 61 |
| 5240 | Montgomery | 1806 | 0.229 | 0.072 | 37 |
| 5380 | Nassau-Suffolk | 1064 | 0.190 | 0.088 | 25 |
| 5520 | New London-Norwich | 1959 | 0.212 | 0.072 | 34 |
| 5600 | New York | 560 | 0.306 | 0.042 | 126 |
| 5640 | Newark | 913 | 0.045 | 0.045 | 22 |
| 5775 | Oakland | 1935 | 0.360 | 0.098 | 25 |
| 5960 | Orlando | 1895 | 0.321 | 0.065 | 55 |
| 6160 | Philadelphia | 783 | 0.217 | 0.054 | 66 |
| 6200 | Phoenix-Mesa | 2547 | 0.282 | 0.073 | 42 |
| 6280 | Pittsburgh | 2729 | 0.167 | 0.051 | 54 |
| 6760 | Richmond-Petersburg | 1762 | 0.167 | 0.063 | 37 |

*continued on next page*

*continued from previous page*

| MSA code | MSA name | HHI | Share reporting credit denied or discouraged | Standard error of estimate | N |
|---|---|---|---|---|---|
| 7040 | St. Louis | 776 | 0.080 | 0.055 | 26 |
| 7160 | Salt Lake City-Ogden | 1493 | 0.167 | 0.046 | 69 |
| 7320 | San Diego | 1468 | 0.350 | 0.076 | 42 |
| 7360 | San Francisco | 2945 | 0.231 | 0.084 | 26 |
| 7510 | Sarasota | 1293 | 0.082 | 0.040 | 53 |
| 7560 | Scranton--Wilkes-Barre--Hazleton | 843 | 0.242 | 0.076 | 34 |
| 7600 | Seattle-Bellevue-Everett | 2034 | 0.111 | 0.062 | 27 |
| 7620 | Sheboygan | 3093 | 0.086 | 0.048 | 37 |
| 7760 | Sioux Falls | 5080 | 0.190 | 0.050 | 64 |
| 8160 | Syracuse | 1614 | 0.283 | 0.067 | 54 |
| 8400 | Toledo | 1717 | 0.083 | 0.047 | 37 |
| 8480 | Trenton | 1669 | 0.179 | 0.074 | 29 |
| 8560 | Tulsa | 828 | 0.236 | 0.058 | 56 |
| 8720 | Vallejo-Fairfield-Napa | 2524 | 0.289 | 0.068 | 47 |
| 8780 | Visalia-Tulare-Porterville | 2342 | 0.185 | 0.076 | 27 |
| 8840 | Washington | 562 | 0.283 | 0.067 | 48 |
| 8920 | Waterloo-Cedar Falls | 1238 | 0.204 | 0.055 | 55 |
| 9240 | Worcester | 2794 | 0.148 | 0.070 | 29 |

Table 8.
Regressions of consumer credit discouragement on market concentration. OLS regressions are of form $I(\textit{credit discouraged})_i^{MSA} = \alpha + \beta * HHI^{MSA} + X_i\Gamma + \varepsilon_i$, where $I(\textit{credit discouraged})_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. $HHI^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, and wealth. IV regressions instrument $HHI^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| Technique | (1) (OLS) | (2) (OLS) | (3) (OLS) | (4) (IV) | (5) (IV) | (6) (IV) |
|---|---|---|---|---|---|---|
| *Variable* | | | | | | |
| HHI (/ 10000) | -1.91* | -2.75** | -2.49*** | -4.38 | -6.04* | -5.08* |
| | (1.08) | (1.11) | (0.92) | (2.74) | (3.34) | (2.58) |
| Age (/ 100) | | -0.85*** | -0.72*** | | -0.86*** | -0.72*** |
| | | (0.04) | (0.05) | | (0.04) | (0.05) |
| *Income variables:* | | | | | | |
| Income (/ 10000) | | -0.40*** | | | -0.41*** | |
| | | (0.04) | | | (0.04) | |
| Income ≥ $ 10000 | | | -0.01 | | | -0.01 |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 20000 | | | -0.09*** | | | -0.09** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 35000 | | | -0.14*** | | | -0.14** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 50000 | | | -0.13*** | | | -0.14** |
| | | | (0.04) | | | (0.03) |
| *Net worth variables:* | | | | | | |
| Net worth (/ 10000) | | 0.01 | | | 0.01 | |
| | | (0.00) | | | (0.00) | |
| Net worth ≥ $ 0 | | | -0.06* | | | -0.06 |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 10000 | | | -0.09** | | | -0.09* |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 25000 | | | -0.18*** | | | -0.18*** |
| | | | (0.03) | | | (0.03) |
| Net worth ≥ $ 100000 | | | -0.21*** | | | -0.21*** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 250000 | | | -0.18*** | | | -0.18*** |
| | | | (0.04) | | | (0.04) |
| Constant | 0.26*** | 0.76*** | 0.79*** | 0.30*** | 0.82*** | 0.83*** |
| | (0.02) | (0.04) | (0.05) | (0.04) | (0.07) | (0.05) |
| R2 | 0.002 | 0.141 | 0.172 | - | 0.135 | 0.168 |
| N | 2553 | 2553 | 2553 | 2547 | 2547 | 2547 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 9.

Regressions of consumer credit discouragement on market concentration. Columns (1)-(3) present OLS regressions of form I(*credit discouraged*)$_i^{MSA}$ = $\alpha + \beta$*HHI$^{MSA}$ + $X_i\Gamma + \varepsilon_i$ , where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports having been denied a loan in the past 5 years. Columns (4)-(6) present OLS regressions of form I(*credit discouraged*)$_i^{MSA}$ = $\alpha + \beta$*HHI$^{MSA}$ + $X_i\Gamma + \varepsilon_i$ , where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports not having for credit because of the anticipation of being denied a loan. HHI$^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, and wealth. IV regressions instrument HHI$^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable is TURN DOWN only | | | Dependent variable is DON'T ASK only | | |
| Technique | (OLS) | (OLS) | (OLS) | (OLS) | (OLS) | (OLS) |
| *Variable* | | | | | | |
| HHI (/ 10000) | -0.91 | -1.44* | -1.49* | -1.27* | -1.85** | -1.49** |
| | (0.82) | (0.85) | (0.78) | (0.75) | (0.77) | (0.67) |
| Age (/ 100) | | -0.66*** | -0.53** | | -0.46*** | -0.40*** |
| | | (0.04) | (0.06) | | (0.04) | (0.04) |
| *Income variables:* | | | | | | |
| Income (/ 10000) | | -0.23*** | | | -0.29*** | |
| | | (0.03) | | | (0.04) | |
| Income ≥ $ 10000 | | | 0.04* | | | -0.05* |
| | | | (0.02) | | | (0.02) |
| Income ≥ $ 20000 | | | 0.00 | | | -0.12*** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 35000 | | | -0.04 | | | -0.13*** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 50000 | | | -0.05 | | | -0.12*** |
| | | | (0.03) | | | (0.03) |
| *Net worth variables:* | | | | | | |
| Net worth (/ 10000) | | 0.00 | | | 0.05 | |
| | | (0.04) | | | (0.04) | |
| Net worth ≥ $ 0 | | | -0.02 | | | -0.07** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 10000 | | | -0.04 | | | -0.08* |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 25000 | | | -0.13*** | | | -0.13*** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 100000 | | | -0.15*** | | | -0.14*** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 250000 | | | -0.14*** | | | -0.12*** |
| | | | (0.04) | | | (0.04) |
| Constant | 0.19* | 0.57*** | 0.53*** | 0.14*** | 0.42*** | 0.50* |
| | (0.02) | (0.04) | (0.04) | (0.02) | (0.04) | (0.03) |
| R2 | 0.000 | 0.096 | 0.116 | 0.001 | 0.081 | 0.114 |
| N | 2553 | 2553 | 2553 | 2553 | 2553 | 2553 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 10.

Regressions of consumer credit discouragement on market concentration, including controls for state-level bankruptcy exemptions. OLS regressions are of form $I(\textit{credit discouraged})_i^{MSA} = \alpha + \beta * HHI^{MSA} + X_i\Gamma + \varepsilon_i$ , where $I(\textit{credit discouraged})_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. $HHI^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, and wealth. IV regressions instrument $HHI^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| Technique | (1) (OLS) | (2) (OLS) | (3) (OLS) | (4) (IV) | (5) (IV) | (6) (IV) |
|---|---|---|---|---|---|---|
| *Variable* | | | | | | |
| HHI (/ 10000) | -2.97** | -3.66*** | -3.47*** | -4.15* | -5.68** | -5.06** |
| | (1.15) | (1.17) | (0.98) | (2.14) | (2.55) | (1.97) |
| Age (/ 100) | | -0.84*** | -0.71*** | | -0.84*** | -0.70*** |
| | | (0.04) | (0.05) | | (0.05) | (0.05) |
| *Bankruptcy exemption variables:* | | | | | | |
| Exemption ≥ $ 10000 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 |
| | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) |
| Exemption ≥ $ 25000 | 0.09** | 0.08** | 0.08** | 0.09** | 0.09** | 0.09** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Exemption ≥ $ 50000 | 0.05 | 0.07 | 0.06 | 0.06 | 0.08 | 0.08 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) | (0.05) |
| Exemption ≥ $100000 | 0.06 | 0.05 | 0.06* | 0.07 | 0.05 | 0.06* |
| | (0.04) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| *Income variables:* | | | | | | |
| Income (/ 10000) | | -0.40*** | | | -0.40*** | |
| | | (0.04) | | | (0.04) | |
| Income ≥ $ 10000 | | | -0.01 | | | -0.01 |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 20000 | | | -0.09*** | | | -0.09** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 35000 | | | -0.14*** | | | -0.13** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 50000 | | | -0.12*** | | | -0.13** |
| | | | (0.04) | | | (0.04) |
| *Net worth variables:* | | | | | | |
| Net worth (/ 10000) | | 0.00 | | | 0.00 | |
| | | (0.00) | | | (0.00) | |
| Net worth ≥ $ 0 | | | -0.06* | | | -0.07* |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 10000 | | | -0.09** | | | -0.09** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 25000 | | | -0.18*** | | | -0.18*** |
| | | | (0.03) | | | (0.03) |
| Net worth ≥ $ 100000 | | | -0.22*** | | | -0.22*** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 250000 | | | -0.20*** | | | -0.20*** |
| | | | (0.04) | | | (0.05) |
| Constant | 0.25*** | 0.74*** | 0.77*** | 0.27*** | 0.77*** | 0.79*** |
| | (0.03) | (0.04) | (0.05) | (0.04) | (0.06) | (0.05) |
| R2 | 0.008 | 0.145 | 0.172 | 0.007 | 0.142 | 0.174 |
| N | 2553 | 2553 | 2553 | 2547 | 2547 | 2547 |

* Significant at 10% level.

* Significant at 5% level.

* Significant at 1% level.

Table 11.

Regressions of consumer credit discouragement on market concentration, including additional locale-specific controls. OLS regressions are of form I(*credit discouraged*)$_i^{MSA}$ = $\alpha + \beta * HHI^{MSA} + X_i\Gamma + \varepsilon_i$, where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. $HHI^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, wealth, state bankruptcy exemptions, and locale-specific controls. IV regressions instrument $HHI^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| Technique | (1) (OLS) | (2) (OLS) | (3) (OLS) | (4) (IV) | (5) (IV) | (6) (IV) |
|---|---|---|---|---|---|---|
| *Variable* | | | | | | |
| HHI (/ 10000) | -3.64*** | -2.32** | -3.36*** | -5.24** | -3.40* | -4.86** |
| | (0.82) | (0.91) | (0.80) | (2.02) | (2.02) | (2.05) |
| Age (/ 100) | -0.72*** | -0.72*** | -0.72*** | -0.71*** | -0.71*** | -0.71*** |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) |
| *Locale* | | | | | | |
| Central cities of 10 largest MSAs | 0.07 | -0.01 | 0.04 | 0.07 | -0.00 | 0.04 |
| | (0.05) | (0.06) | (0.06) | (0.05) | (0.07) | (0.06) |
| Central cities of other MSAs | 0.07 | 0.02 | 0.05 | 0.08 | 0.04 | 0.07 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) | (0.05) |
| Suburbs of 10 largest MSAs | 0.04 | -0.03 | 0.01 | 0.03 | -0.02 | 0.01 |
| | (0.05) | (0.06) | (0.05) | (0.05) | (0.06) | (0.05) |
| Suburbs of other MSAs | 0.03 | -0.02 | 0.01 | 0.03 | -0.01 | 0.02 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) | (0.05) |
| Other areas within 50 miles of MSA center | -0.01 | -0.04 | -0.02 | -0.01 | -0.04 | -0.02 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) | (0.05) |
| *MSA size:* | | | | | | |
| Log(MSA size) (/ 100) | | 2.42** | | | 2.01* | |
| | | (1.05) | | | (1.20) | |
| MSA size ≥ 1 million | | | 2.82 | | | 2.20 |
| | | | (2.46) | | | (2.52) |
| Constant | 0.71*** | 0.43*** | 0.73*** | 0.74*** | 0.49*** | 0.74*** |
| | (0.05) | (0.14) | (0.05) | (0.05) | (0.16) | (0.05) |
| *Other dummy variables:* | | | | | | |
| *Bankruptcy exemptions* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Income* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Net worth* | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.180 | 0.182 | 0.181 | 0.174 | 0.181 | 0.179 |
| N | 2553 | 2553 | 2553 | 2547 | 2547 | 2547 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 12.
Regressions of consumer credit discouragement on market concentration. OLS regressions are of form I(*credit discouraged*)$_i^{MSA}$ = $\alpha + \beta$*I($HHI^{MSA} \geq 1800$) + $X_i\Gamma + \varepsilon_i$ , where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. I($HHI^{MSA} \geq 1800$) is set equal to 1 if the Herfindahl Index in the household's MSA's commercial banking sector equals or exceeds 1800, and $X_i$ includes controls for age, income, and wealth. IV regressions instrument $HHI^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| Technique | (1) (OLS) | (2) (OLS) | (3) (OLS) | (4) (IV) | (5) (IV) | (6) (IV) |
|---|---|---|---|---|---|---|
| *Variable* | | | | | | |
| HHI ≥ 1800 (/100) | -5.03** | -5.45** | -5.21*** | -18.67** | -22.90** | -19.38** |
| | (2.21) | (2.20) | (1.93) | (9.05) | (9.60) | (7.78) |
| Age (/ 100) | | -0.84*** | -0.70*** | | -0.83*** | -0.69*** |
| | | (0.04) | (0.05) | | (0.04) | (0.06) |
| *Bankruptcy exemption variables:* | | | | | | |
| Exemption ≥ $ 10000 | 0.02 | 0.02 | 0.02 | 0.04 | 0.05 | 0.04 |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| Exemption ≥ $ 25000 | 0.09** | 0.08** | 0.08** | 0.13** | 0.14** | 0.13*** |
| | (0.04) | (0.04) | (0.03) | (0.05) | (0.06) | (0.05) |
| Exemption ≥ $ 50000 | 0.05 | 0.07 | 0.07 | 0.13 | 0.17 | 0.15 |
| | (0.05) | (0.05) | (0.05) | (0.10) | (0.11) | (0.10) |
| Exemption ≥ $100000 | 0.07 | 0.05 | 0.06* | 0.10** | 0.10* | 0.10* |
| | (0.04) | (0.03) | (0.03) | (0.06) | (0.06) | (0.05) |
| *Income variables:* | | | | | | |
| Income (/ 10000) | | -0.39*** | | | -0.41*** | |
| | | (0.04) | | | (0.05) | |
| Income ≥ $ 10000 | | | -0.01 | | | -0.01 |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 20000 | | | -0.09*** | | | -0.09*** |
| | | | (0.03) | | | (0.03) |
| Income ≥ $ 35000 | | | -0.13*** | | | -0.13*** |
| | | | (0.03) | | | (0.04) |
| Income ≥ $ 50000 | | | -0.12*** | | | -0.13*** |
| | | | (0.04) | | | (0.04) |
| *Net worth variables:* | | | | | | |
| Net worth (/ 10000) | | 0.00 | | | 0.00 | |
| | | (0.00) | | | (0.00) | |
| Net worth ≥ $ 0 | | | -0.06* | | | -0.06* |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 10000 | | | -0.09** | | | -0.08* |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 25000 | | | -0.18*** | | | -0.18*** |
| | | | (0.03) | | | (0.03) |
| Net worth ≥ $ 100000 | | | -0.22*** | | | -0.22*** |
| | | | (0.04) | | | (0.04) |
| Net worth ≥ $ 250000 | | | -0.20*** | | | -0.20*** |
| | | | (0.04) | | | (0.05) |
| Constant | 0.21*** | 0.69*** | 0.72*** | 0.23*** | 0.71*** | 0.73* |
| | (0.02) | (0.03) | (0.04) | (0.03) | (0.05) | (0.04) |
| R2 | 0.007 | 0.144 | 0.175 | . | 0.107 | 0.151 |
| N | 2553 | 2553 | 2553 | 2547 | 2547 | 2547 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 13.

Regressions of consumer credit discouragement on market concentration, including additional demographic controls. OLS regressions are of form I(*credit discouraged*)$_i^{MSA} = \alpha + \beta * HHI^{MSA} + X_i\Gamma + \varepsilon_i$, where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. $HHI^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, wealth, age, race, education, and state bankruptcy exemptions. IV regressions instrument $HHI^{MSA}$ with a set of variables describing state-level political control. All standard errors corrected for MSA-level clustering.

| Technique | (1) (OLS) | (2) (OLS) | (3) (OLS) | (4) (IV) | (5) (IV) | (6) (IV) |
|---|---|---|---|---|---|---|
| *Variable* | | | | | | |
| HHI (/ 10000) | -3.47*** | -3.19*** | -2.67*** | -5.06** | -4.79** | -2.99* |
| | (0.98) | (1.00) | (1.01) | (1.97) | (2.13) | (1.69) |
| Age (/ 100) | -0.71*** | -0.68*** | -0.69*** | -0.70*** | -0.68*** | -0.69*** |
| | (0.05) | (0.06) | (0.06) | (0.05) | (0.06) | (0.06) |
| *Education dummy variables:* | | | | | | |
| 9-12 Years of education | | 0.01 | 0.01 | | 0.01 | 0.01 |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| High school diploma | | 0.02 | 0.02 | | 0.02 | 0.02 |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| Some college | | 0.06* | 0.05 | | 0.06 | 0.05 |
| | | (0.04) | (0.04) | | (0.04) | (0.04) |
| College degree | | 0.01 | 0.01 | | 0.01 | 0.01 |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| *Race dummy variables:* | | | | | | |
| Black except Hispanic | | 0.13*** | 0.14*** | | 0.13*** | 0.14*** |
| | | (0.03) | (0.03) | | (0.03) | (0.03) |
| Hispanic | | -0.01 | -0.02 | | -0.02 | -0.02 |
| | | (0.05) | (0.04) | | (0.05) | (0.04) |
| American Indian | | 0.24* | 0.23* | | 0.23* | 0.23* |
| | | (0.13) | (0.13) | | (0.13) | (0.13) |
| Asian or Pacific Islander | | -0.00 | -0.01 | | -0.01 | -0.01 |
| | | (0.09) | (0.09) | | (0.09) | (0.09) |
| *Region dummy variables:* | | | | | | |
| North central | | | -0.05* | | | -0.05* |
| | | | (0.02) | | | (0.02) |
| South | | | -0.02 | | | -0.03 |
| | | | (0.03) | | | (0.03) |
| West | | | 0.01 | | | 0.16 |
| | | | (0.03) | | | (0.03) |
| Constant | 0.77*** | 0.68*** | 0.70*** | 0.79*** | 0.70*** | 0.71*** |
| | (0.05) | (0.06) | (0.08) | (0.05) | (0.07) | (0.08) |
| *Other dummy variables:* | | | | | | |
| *Bankruptcy exemptions* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Income* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Net worth* | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.176 | 0.190 | 0.192 | 0.174 | 0.188 | 0.190 |
| N | 2553 | 2553 | 2553 | 2547 | 2547 | 2547 |

* Significant at 10% level.

* Significant at 5% level.

* Significant at 1% level.

Table 14.

Regressions of consumer credit discouragement on market concentration, by age of household head. OLS regressions are of form I(*credit discouraged*)$_i^{MSA}$ = $\alpha + \beta$*HHI$^{MSA}$ + $X_i\Gamma + \varepsilon_i$ , where I(*credit discouraged*)$_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. HHI$^{MSA}$ is the Herfindahl Index in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, wealth, age, race, education, and state bankruptcy exemptions. IV regressions instrument HHI$^{MSA}$ with a set of variables describing state-level political control.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | Household head < 40 | | | Household head ≥ 40 | | |
| Technique | (OLS) | (IV) | (IV) | (OLS) | (IV) | (IV) |
| *Variable* | | | | | | |
| HHI (/ 10000) | -4.83*** | -5.93** | -3.14 | -0.80 | -3.14 | -2.20 |
| | (1.29) | (2.54) | (2.18) | (1.06) | (1.93) | (1.66) |
| Age (/ 100) | -0.31 | -0.26 | -0.30 | -0.59*** | -0.59*** | -0.58*** |
| | (0.27) | (0.27) | (0.27) | (0.10) | (0.08) | (0.10) |
| *Education dummy variables:* | | | | | | |
| 9-12 Years of education | 0.08 | 0.08 | 0.08 | -0.01 | -0.01 | -0.01 |
| | (0.11) | (0.11) | (0.11) | (0.03) | (0.03) | (0.03) |
| High school diploma | 0.06 | 0.06 | 0.06 | -0.01 | -0.01 | -0.01 |
| | (0.10) | (0.10) | (0.10) | (0.03) | (0.03) | (0.03) |
| Some college | 0.09 | 0.09 | 0.09 | 0.04 | 0.04 | 0.03 |
| | (0.10) | (0.10) | (0.10) | (0.03) | (0.03) | (0.03) |
| College degree | 0.01 | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 |
| | (0.10) | (0.10) | (0.11) | (0.03) | (0.03) | (0.03) |
| *Race dummy variables:* | | | | | | |
| Black except Hispanic | 0.14*** | 0.14*** | 0.15*** | 0.12*** | 0.12*** | 0.12*** |
| | (0.04) | (0.05) | (0.05) | (0.04) | (0.03) | (0.04) |
| Hispanic | -0.05 | -0.05 | -0.05 | 0.01 | -0.00 | 0.00 |
| | (0.07) | (0.07) | (0.07) | (0.05) | (0.05) | (0.05) |
| American Indian | 0.60*** | 0.60*** | 0.60*** | -0.15*** | -0.16*** | -0.15*** |
| | (0.07) | (0.07) | (0.07) | (0.04) | (0.04) | (0.04) |
| Asian or Pacific Islander | -0.00 | 0.01 | 0.00 | -0.07 | -0.07 | -0.07 |
| | (0.11) | (0.10) | (0.10) | (0.14) | (0.14) | (0.14) |
| *Region dummy variables:* | | | | | | |
| North central | -0.07* | | -0.08** | -0.03 | | -0.02 |
| | (0.04) | | (0.04) | (0.02) | | (0.03) |
| South | -0.03 | | -0.02 | 0.00 | | -0.03 |
| | (0.04) | | (0.06) | (0.03) | | (0.03) |
| West | 0.03 | | 0.03 | 0.01 | | 0.01 |
| | (0.05) | | (0.06) | (0.02) | | (0.03) |
| Constant | 0.61*** | 0.59*** | 0.57*** | 0.59*** | 0.59*** | 0.61*** |
| | (0.16) | (0.16) | (0.17) | (0.09) | (0.08) | (0.09) |
| *Other dummy variables:* | | | | | | |
| *Bankruptcy exemptions* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Income* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Net worth* | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.135 | 0.130 | 0.133 | 0.124 | 0.117 | 0.120 |
| N | 1130 | 1127 | 1127 | 1423 | 1420 | 1420 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 15.

Regressions of consumer credit discouragement on market concentration, using different measures of market concentration. OLS regressions are of form $I(\textit{credit discouraged})_i^{MSA} = \alpha + \beta * CONC^{MSA} + X_i\Gamma + \varepsilon_i$, where $I(\textit{credit discouraged})_i^{MSA}$ is set equal to 1 if the respondent reports having either been denied a loan in the past 5 years or has not applied for credit because of the anticipation of being denied a loan. $CONC^{MSA}$ is the measure of financial market concentration in the household's MSA's commercial banking sector, and $X_i$ includes controls for age, income, wealth, age, race, education, and state bankruptcy exemptions. All standard errors corrected for MSA-level clustering.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Technique | (OLS) | (OLS) | (OLS) | (OLS) | (OLS) |
| Measure of concentration | HHI, commercial banks | Dummy for commercial bank HHI ≥ 1800 | HHI, all depository institutions | 3-firm concentration ratio, commercial banks | 3-firm concentration ratio, all depository institutions |
| *Variable* | | | | | |
| HHI (/ 10000) | -3.47*** | -5.20*** | -4.56*** | -1.98*** | -2.18*** |
| | (0.98) | (1.93) | (1.38) | (0.64) | (0.74) |
| Age (/ 100) | -0.71*** | -0.70*** | -0.71*** | -0.71*** | -0.71*** |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.06) |
| Constant | 0.77*** | 0.72*** | 0.77*** | 0.84*** | 0.81*** |
| | (0.05) | (0.05) | (0.05) | (0.07) | (0.06) |
| *Dummy variables:* | | | | | |
| *Bankruptcy exemptions* | Yes | Yes | Yes | Yes | Yes |
| *Income* | Yes | Yes | Yes | Yes | Yes |
| *Net worth* | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.176 | 0.175 | 0.177 | 0.176 | 0.176 |
| N | 2553 | 2553 | 2553 | 2553 | 2553 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

Table 16.
Regressions of consumer credit interest rates on age, by concentration of market. OLS regressions are of form $INTRATE_i^{MSA} = \alpha + \beta * AGE_i^{MSA} + X_i\Gamma + \varepsilon_i$, where $INTRATE_i^{MSA}$ is the interest rate on consumer and credit card borrowing. $X_i$ includes controls for income and wealth.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sample | Concentrated MSAs (HHI ≥ 1800) | | | Competitive MSAs (HHI < 1800) | | |
| Technique | (OLS) | (OLS) | (OLS) | (OLS) | (OLS) | (OLS) |
| *Variable* | | | | | | |
| Age (/10) | -0.32 | -0.27 | -0.31 | -0.60** | -0.69** | -0.64** |
| | (0.21) | (0.24) | (0.26) | (0.15) | (0.18) | (0.18) |
| *Dummy variables:* | | | | | | |
| Bankruptcy exemptions | | Yes | Yes | | Yes | Yes |
| Income | | Yes | Yes | | Yes | Yes |
| Net worth | | Yes | Yes | | Yes | Yes |
| Education | | | Yes | | | Yes |
| Race | | | Yes | | | Yes |
| Region | | | Yes | | | Yes |
| Constant | 16.30** | 12.08** | 9.66** | 16.64** | 15.18** | 12.34** |
| | (0.92) | (2.50) | (2.81) | (0.66) | (1.48) | (1.70) |
| N | 0.004 | 0.063 | 0.075 | 1062 | 1062 | 1062 |
| R2 | 570 | 570 | 570 | 0.014 | 0.057 | 0.084 |

* Significant at 10% level.
* Significant at 5% level.
* Significant at 1% level.

*Chapter 3*
**Do after-tax returns affect mutual fund inflows?**

### 3.1. Introduction

Mutual funds in the United States are taxed under a specialized set of rules. First, they are required to "pass through" dividends and capital gain realizations to their investors. This restricts the fund investor's ability to exploit tax-timing strategies of the type discussed by Stiglitz (1983), Constantinides (1984), and Dammon and Spatt (1996). Dickson and Shoven (1995) claim that in the early 1990s, some mutual fund managers pursued realization strategies that imposed unnecessarily large tax burdens on shareholders. One example would be choosing to sell the lowest-basis tranche of a security in their portfolio, thereby imposing a larger-than-necessary capital gains tax burden on their taxable investors. The Congressional Budget Office (1999) estimates that mutual fund capital gain distributions, which exceeded $180 billion in 1997, contributed roughly $15 billion to federal capital gains tax revenues for that year.

Second, capital gain and dividend realizations are allocated equally across mutual fund shares, regardless of when the shares were created. New fund investors are allocated the same share of capital gain realizations as old investors, even though their shares in the fund may have been created after the gains being realized accrued to the fund. Investors who purchase shares in funds that have accrued but unrealized capital gains therefore face the prospect of distributions of realized capital gains during the period for which they hold the fund. Accrued but unrealized gains are often called a "capital gain overhang." Barclay, Pearson, and Weisbach (1998) present evidence that funds with larger overhangs have lower net inflows than other funds, and Warther (1998) develops a theoretical model that is designed to explain when mutual funds might choose to build up an overhang of unrealized gains.

The tax issues surrounding mutual fund investment have become increasingly significant as mutual funds have become a more important channel for individual equity ownership. Data from the 1998 Survey of Consumer Finances reported in Kennickell, Starr-McCluer, and Surette

(2000) show that 16.5 percent of families now own mutual funds, excluding ownership of such funds through retirement accounts. This compares with 19.2 percent of families with direct ownership of corporate stock. Many other families own mutual funds through retirement accounts. The tax implications of mutual fund ownership through retirement plans are different from the implications of direct fund ownership, since realized gains are not taxed until assets are withdrawn from the retirement account, and then they are taxed as ordinary income.

The current study evaluates the impact of personal taxation on the returns earned by mutual fund investors. It then considers how the tax burden on different funds affects investor purchases and redemptions of shares in these funds. There is a large previous literature on the relationship between fund performance and subsequent net inflows, including work by Ippolito (1992), Hendricks, Patel, and Zeckhauser (1994), Chevalier and Ellison (1996), Sirri and Tufano (1997), and Warther (1997). This literature uniformly finds that at the individual fund level, net inflows are positively related to past performance. Because there is some persistence in fund performance, Gruber (1996) finds that an inflow-weighted-average of mutual fund returns generates a higher average return than a fund-weighted return. The precise explanation of persistence in fund returns, and the implications of such persistence for investor behavior, is still an open issue. Carhart (1997) shows that persistence in fund expenses and medium-term persistence in underlying asset returns, rather than persistence in stock-picking ability, explain most of the persistence in fund returns that has been identified in previous studies.

Virtually all of the existing studies of returns and fund inflows focus on pretax returns. In the current paper, we extend this work in three ways. First, we consider the relationship between net inflows and both realized and potential individual income tax burdens. We find that funds that deliver returns that are more heavily taxed, i.e. come in the form of dividends or realized capital gains, have lower subsequent inflows than funds with similar pretax returns that are not so heavily taxed. After-tax return measures outperform pretax returns in explaining net inflows.

Second, we explore the factors that explain the cross-sectional variation in the tax burdens that domestic equity mutual funds impose on their investors. We consider the impact of fund turnover, the tenure of the management team, investment style, and other factors in contributing to the divergence between pretax and after-tax return. Turnover has a large effect on capital gain realizations, and new fund managers tend to impose large capital gains tax liabilities on investors by realizing accrued capital gains. We also confirm Barclay, Pearson, and Weisbach's (1998) result that funds with larger stocks of unrealized capital gains have smaller net inflows, conditional on their past return performance.

Finally, we move beyond the study of net fund inflows to explore the relationship between fund performance, gross fund inflows, and gross redemptions. Previous studies have focused on net fund flows because data on gross flows is not as readily available as data on net flows. We collect new data from SEC filings that describe gross inflows and gross outflows, and we use these data to evaluate how investors adjust their investment decisions in response to differences in after-tax returns and prospective capital gains tax liability.

The paper is divided into six sections. The first describes how we construct risk-adjusted and tax-adjusted mutual fund returns. Mutual fund investors are heterogeneous, and we are forced to make some simplifying assumptions about the tax burdens on fund investors. This section also describes our database of fund returns, and reports summary statistics on the level and persistence of pretax and after-tax returns of a large sample of equity mutual funds in the 1990s. Section two explores the determinants of the tax burdens on the returns to different equity mutual funds. We investigate how various fund characteristics are correlated with 'tax efficiency,' and find several aspects of fund behavior that have substantial predictive power in explaining investor tax burdens.

The third section describes the data set that we use to measure annual net inflows to U.S. equity mutual funds, and it presents summary information on net flows during the sample period that we consider. In section four, we report our basic findings on the relationship between fund returns, potential capital gains distributions, and fund net inflows. We compare the relative predictive power of pretax and after-tax returns in a range of regression models for fund inflows, controlling for a variety of other factors that may affect investor behavior. The results support the notion that tax burdens affect fund inflows, and the findings are robust with respect to the inclusion of many control variables. Section five presents our analysis of how gross inflows and gross outflows vary with past performance. We describe the data that we have collected on gross flows for a large sample of funds, and we study whether gross redemptions, or gross inflows, or both, are affected by fund tax burdens and unrealized capital gains. We find that funds with substantial capital gains "tax overhang" experience both lower inflows, as tax-sensitive investors avoid such funds, and lower outflows, as investors are reluctant to sell these funds and realize the associated capital gains. A brief conclusion suggests several directions for future work.

### 3.2. Measuring pretax and after-tax returns on mutual funds

Mutual funds generate three types of taxable returns for their investors. These are dividends, which are passed through to the investor and taxed as ordinary income, short-term realized capital gains, which are also taxed as ordinary income, and long-term capital gain realizations, which are taxed at the prevailing long-term capital gains tax rate. Even if an investor has held a mutual fund for less than the holding period that is required for long-term capital gains tax status for other assets, a mutual fund's long-term capital gain realizations are still taxed as long-term gains. (In 1997 and 1998, it was also possible for mutual funds to generate a fourth type of taxable income, 'intermediate term' capital gains, that were taxed at a rate (28 percent) between the ordinary income tax rate and the long-term gains rate.) In addition to these taxable returns, equity mutual funds may also generate "untaxed" returns in the form of unrealized capital gains. The tax burden on such returns is a function of investor behavior rather than fund manager behavior. Provided the investor does not sell his shares in the fund, there is no tax due on unrealized gains.

Most discussions of mutual fund returns, and most academic studies of fund behavior and return performance, focus on pretax returns. Such returns are just the sum of the four return components described above. Recently, however, there has been increased attention to the after-tax returns on different mutual funds. Dickson and Shoven (1995) and construct after-tax measures of fund returns for hypothetical investors, and they show that the relative standing of various funds in rankings of fund returns can be quite sensitive to the choice between pretax and after-tax returns. Morningstar, a leading mutual fund information service, has recently started to publish post-tax return measures in its fund performance database. In 1999, the Vanguard mutual fund family began to report returns to shareholders on both a pre-tax and after-tax basis.

Despite the interest in after-tax returns, there is no consensus on how to measure such returns. There are important differences across investors in their tax status, so it is not possible to create a "one size fits all" measure of after-tax fund performance. We follow Dickson and Shoven (1995) in constructing after-tax returns for hypothetical upper-income investors. Because most mutual fund investors face marginal tax rates on dividend and interest income, and on short-term capital gains, of between 28 and 39.6 percent, and long-term capital gains tax rates of 20 percent, the degree of tax rate heterogeneity is limited. Ignoring taxes completely is likely to result in a larger mis-statement of after-tax returns than adjusting returns with imprecise tax rates.

To formalize our tax calculations for mutual fund returns, we define a fund's total pretax return as

(1) $$R_p = d + g_s + g_l + u$$

where d denotes dividend payout as a fraction of the beginning-of-year net asset value, $g_s$ denotes realized short-term capital gains, $g_l$ denotes realized long-term gains, and u denotes unrealized capital gains. Consider a taxable investor who faces a tax rate of $\tau_d$ on dividends and short-term realized gains and a rate of $\tau_{cg}$ on realized long-term capital gains. Assume that the effective accrual tax rate on unrealized capital gains, which as Poterba (1999) explains is the present discounted value of the future taxes that will be due on these gains, is $\tau_{ucg}$. We define the fund's one-year 'buy and hold' after-tax return as

(2) $$R_a = (1 - \tau_d) * (d + g_s) + (1 - \tau_{cg}) * g_l + (1 - \tau_{ucg}) * u.$$

We assume an effective tax rate of $\tau_{ucg} < \tau_{cg}$ on gains that are not distributed during the current calendar year. If the mutual fund never realizes these gains, and if the investor holds his shares until he dies, so that the resulting capital gains tax liability is extinguished through basis step-up at death, then effective tax rate on these undistributed gains would be zero. In practice, it is likely both that the investor will sell mutual fund shares before death, and that the mutual fund manager will realize at least part of the gain in future years. The effective tax rate on undistributed accruing gains therefore depends on the fund manager's realization strategy and the investor's investment horizon. It also depends on the rate of return at which the investor discounts future tax liabilities.

In most of our empirical work, we assume a value of 0.10 for $\tau_{ucg}$. This is half the statutory tax rate on realized long-term gains, and it is broadly consistent with effective tax rate calculations using a range of plausible values for realization rates and discount rates. Our empirical results are quite robust to alternative assumptions about this tax parameter, including an assumption that it equals zero. The difficulty of measuring the tax burden on unrealized gains is an inherent limitation of our focus on annual fund returns. Because the after-tax return on a long-term investment can only be measured precisely over a long holding period, there is necessarily some approximation involved in assigning one-period tax burdens to fund investments.

The problem of approximating future tax burdens would vanish if we assumed that the mutual fund investor sold his shares at the end of the calendar year. In this case, the after-tax return would be

(2') $$R_a' = (1 - \tau_d) * (d + g_s) + (1 - \tau_{cg})*(g_l + u).$$

In this case all unrealized gains or losses from the fund's investments in the current year are taxable in the current year. The option to sell mutual fund shares provides investors with an important protection against purchasing a mutual fund and facing a large capital gain distribution. If the fund distributes gains that were accrued before the investor purchased the fund, this will reduce the net asset value of the fund's shares. In this case the investor can sell the shares, realize a capital <u>loss</u> on the mutual fund shares, and use this loss to offset the gain that was passed through from the fund. This realization strategy is often ignored in discussions of the potential tax burdens associated with capital gain 'overhangs.'

We use the difference between the pretax return in (1) and the after-tax return in (2) to measure the fund's tax burden. We could scale this by the fund's pretax return, thereby constructing an 'effective tax rate,' but we do not follow this approach because it runs into difficulty when a fund experiences negative returns. Our measure of the fund's tax burden is therefore

$$T = \tau_d * (d + g_s) + \tau_{cg} * g_l + \tau_{ucg} * u. \tag{3}$$

To construct this measure of a fund's tax burden, we need data on both long-term and short-term capital gain realizations. Morningstar has provided us with historical data on the disaggregated capital gain components for the funds that survived to January 1999. However, for mutual funds that were traded earlier in the 1990s, but that disappeared due to merger or liquidation prior to January 1999, we have only been able to obtain data on total capital gain distributions. We thus face a choice between studying a sample of funds that is likely to be subject to survivorship bias but for which we have accurate measures of tax burdens, or studying a sample of funds with very little survivorship bias but with inaccurate tax burden data. Previous work, cited in Carpenter and Lynch (1999), suggests that funds with poor returns are most likely to be merged or liquidated and that this may induce biases in studying the persistence of fund returns or inflows. Most of our analysis therefore uses data on all funds that were traded during our sample period, but does not distinguish between long-term and short-term capital gain realizations. This imparts some measurement error to our analysis of tax burdens.

When we do not know the disaggregate composition of realized gains, we assume that all gains are long-term. We therefore define after-tax returns as

(2'') $$R''_a = (1 - \tau_d)*d + (1 - \tau_{cg})*(g_l + g_s) + (1 - \tau_{ucg})*u$$

and we measure the tax burden as

(3'') $$T'' = \tau_d * d + \tau_{cg} * (g_l + g_s) + \tau_{ucg} * u.$$

To assess the magnitude and direction of any bias that results from aggregating short-term and long-term gain realizations, we compare our basic findings for one year, 1999, using measures (2) and (3) as well as (2'') and (3'') to define after-tax returns. Fortunately, the results of this comparison suggest that using a noisy tax measure may not have a large impact on our results.

A critical question in defining the after-tax return concerns the appropriate tax rates to use in evaluating (2) and (3). It is difficult to know the precise tax rates facing mutual fund investors. Information from tax returns, which can be used to compute 'weighted average' tax rates on interest or dividend income such as those used in Poterba (1998), does not identify the income from mutual funds as opposed to other investments. Other sources of information on asset ownership, such as the Survey of Consumer Finances (SCF), provide only sketchy information about household attributes that may affect marginal tax rates. Poterba and Samwick (1999) attempt to impute marginal tax rates to households in the SCF, and they discuss the potential pitfalls of such an approach. One of the most important problems is that it is not possible to identify the characteristics of the particular mutual funds that each household owns. If high tax rate households tend to invest in mutual funds that are more tax efficient than the funds held by lower tax rate households, calculations based simply on mutual fund ownership may mis-state actual tax burdens.

In our estimates of the tax burden on mutual fund returns, we assume that dividend income and short-term capital gain realizations are taxed at the marginal personal income tax rate of 31 percent. This is equivalent to assuming that the 'marginal investor' receiving income from mutual funds has 1998 taxable income of between $102,300 and $155,950. We further assume that all capital gains are long term and that they are taxed at the prevailing maximum long-term capital gains tax rate, which is 20 percent in 1998. Our calculations assume the same tax rates in computing the after-tax returns for all funds. This ignores the possibility that investors form clienteles, with taxable investors purchasing one set of funds, and tax-exempt investors purchasing another set. We do not currently have the data on fund ownership that would be needed to investigate the importance of clientele formation.

Table 1 presents summary information on the direct ownership of mutual funds from the 1995 SCF. Of the 12.2 million households that owned taxable mutual funds in 1995, more than three-quarters had annual income of less than $100,000. These households owned 54 percent of all taxable mutual fund assets. The table also shows that while families with incomes of more than $250,000 represent only 2.9 percent of mutual fund investors, they hold 18.5 percent of the assets in taxable mutual funds. These statistics are generally supportive of our use of marginal tax rates that correspond to households in the upper part, but not the top, of the income distribution.

Table 1 also shows that there are substantial differences across income categories in the probability that a household owns any taxable mutual funds. For households with incomes of less than $50,000, this probability is 7.7 percent, rising to 40.1 percent for households with incomes between $150,000 and $250,000. The probability of owning a taxable mutual fund is <u>lower</u> for those in the highest income category (38.8 percent for those with incomes of $250,000 and above) than for those in the income category just below this level. This pattern stands in contrast to the income-specific ownership patterns for mutual funds held through retirement accounts and for direct stock ownership, both of which show rising ownership probabilities across the income spectrum.

### 3.3. Data on mutual fund returns

We restrict our analysis to U.S. domestic equity mutual funds, and we obtain data on fund returns from the six January releases of the Morningstar mutual fund database published between 1994 and 1999. Because funds that disappear through merger or liquidation are removed from subsequent editions of the Morningstar database, using the end-of-sample data release for retrospective analysis of fund performance may result in survivorship biases. We avoid this problem, and also obtain additional data on historical values of fund characteristics such as load structure, manager tenure, and fund objective, by merging data from each of the six annual data releases.

Our data set mirrors the set of equity funds available to investors in each year between 1994 and 1999. We begin with the all equity funds in the various Morningstar data files, and we exclude any observations for which Morningstar does not report a ticker symbol, a net asset value, or a value for total fund assets at year-end. We further exclude funds that are identified as bond funds, hybrid funds, international funds, and specialty equity funds, and we limit our analysis to domestic equity funds that are open to new investment from retail customers. These exclusions yield a "potential data sample" of 10,789 fund-year observations, of which 2,984 are in 1998. From this potential data sample, we exclude 3,482 fund-years corresponding to funds with less than three years of historical returns. This limits our sample to funds with established track records. We exclude an additional 36 fund-years in which measured net inflows exceed ten times beginning-of-period size, and five additional fund-years for which Morningstar did not report ratings or information on the median market capitalization of the stocks in the fund's portfolio. The net effect of these exclusions is to leave a sample with 5,866 fund-years of data, of which 1,607 are for 1998. The year-end 1998 market value of the funds in our sample was about $1.5 trillion.

The two most important sample restrictions that we impose are the exclusion of institutional equity funds, which held $182 billion in assets at the end of 1998, and the exclusion of funds that are closed to new investors. Funds that were closed in 1998, such as Fidelity Magellan, held $277 billion in assets. Excluding international stock funds and specialty domestic funds are also substantial restrictions; foreign stock funds accounted for $176 billion in assets at the end of 1998.

### 3.3.1. Summary statistics on pretax and after-tax returns

Table 2 presents summary statistics on the mean and median returns, and the components of returns, for our data sample. These statistics highlight the importance of tax factors in affecting returns to taxable investors. For the 1993-1998 period, the mean pretax return on equity mutual funds (shown in the upper panel of the table) is 17.1 percent per year, while the mean after-tax return is 14.1 percent. The sample period that we consider has been characterized by very favorable returns on the U.S. equity market in general, so our average returns are likely to be significantly higher than those that would be observed over longer sample periods.

Table 2 provides some insight on the reason for the difference between the pretax and after-tax return. Undistributed capital gains generate, on average, a 7.8 percent return for fund shareholders. Heavily taxed dividends average 1.0 percent, and capital gain distributions account for an average pretax return of 8.3 percent. Given our assumptions about the marginal tax rates of the representative mutual fund investor, these pretax returns generate a tax burden of 3.0 percent per year. If we assumed a lower tax burden on undistributed capital gains, the tax burden would be correspondingly lower. If we set this tax rate to zero, the tax burden would average 2.6 percent per year.

Our data confirm Dickson and Shoven's (1995) finding of significant heterogeneity in the tax liabilities associated with different mutual fund investments. The range in the tax burdens between the 75$^{th}$ and 25$^{th}$ percentile funds, when the ranking is by tax burdens, is 2.4 percentage points.

Table 3 presents summary statistics on pretax and after-tax returns for each of the years in our sample period. We show means that weight each mutual fund equally, as well as means that weight funds by their total assets under management. Asset-weighted summary statistics describe the return on the average dollar invested in equity mutual funds better than fund-weighted summary statistics. The first column of Table 3 shows the number of mutual funds in our sample for each year. The next two columns show year-by-year equal-weighted average pretax returns, and average tax burdens. The last two columns show analogous weighted average returns. The results show that returns on large funds have exceeded those on small funds. The asset-weighted mean pretax return is 20.9 percent per year, compared with a mean return of 17.1 percent when funds are weighted equally. The average tax burden is 3.4 percent on an asset-weighted basis, and 3.0 percent on an asset-weighted basis.

The statistics on interquartile ranges in Table 2 suggest significant variation in both returns and tax burdens across funds. Tables 4 and 5 illustrate this heterogeneity in a more immediate way. Table 4 reports the pretax return, tax burden, after-tax return, and unrealized capital gains as a share of assets for the twenty largest funds in our sample for calendar year 1998. Table 5 reports similar statistics for the twenty largest S&P 500 index funds in our sample. While the twenty largest equity funds differ in both characteristics and clientele, the S&P 500 index funds share important similarities.

The data in Table 4 show a wide range of tax burdens for different funds. An investor facing the tax rates that we assume, and holding the American Century-20$^{th}$ Century Ultra Fund in 1998, faced a tax burden of 4.5 percentage points. The same investor holding the Fidelity Blue-Chip Growth fund would have faced a tax burden of 4.0 percent on a comparable pre-tax return, while by holding the Vanguard Index 500 fund, the investor would have faced a tax burden of 3.2 percentage points. (Note that these "tax burdens" include our estimates of the future taxes that will be due on currently unrealized capital gains.)

Table 5 shows striking differences in the after-tax performance of different S&P 500 index funds. This comparison is suggestive of substantial heterogeneity across equity funds more generally, because all of the funds in Table 5 have ostensibly similar investment objectives. The Vanguard Index 500 fund turns in the best after-tax performance. While a number of other funds have after-tax returns that are bunched within 20 basis points of the Vanguard Index 500, several underperform by more than 100 basis points, and two underperform by more than 350 basis points. These differences in part reflect the fact that different index funds have different requirements on the share of fund assets that must be held in stocks that are included in the index. Much of the variation in the after-tax returns across "index funds" reflects variation in pretax returns, but there also appear to be important differences in tax management styles across these funds.

### 3.3.2. Adjusting returns for risk

Our discussion so far has considered returns on different mutual funds without any recognition of potential differences in fund risk characteristics. Since our ultimate objective is to study how returns affect inflows, we need to allow for the differential riskiness of the investment strategies pursued by different funds. One could imagine a spurious relationship between past fund returns and current fund inflows that is driven solely by a relationship between both of these variables and a third factor, which is the fund's risk profile.

Previous researchers have related fund inflows to three different measures of risk-adjusted fund returns: the fund return relative to a market index ($A^m_{it} = R_{it} - R^m_t$); the 'alpha' from a one-factor risk-adjustment model ($A^1_{it} = R_{it} - r_t - \beta^m_{it} * (R^m_t - r_t)$); and the alpha from a multifactor pricing model. Chevalier and Ellison's (1997) analysis of inflows uses the first measure, while Gruber's (1996) study uses alphas from one-factor and four-factor models. Gruber's (1996) four-factor return relationship includes the market return, a bond index return, and returns to portfolios designed to capture market capitalization and growth-value effects.

Carhart's (1997) model is similar to Gruber's (1996), but it also includes a medium-term persistence factor ('momentum') discussed in Jegadeesh and Titman (1993).

In our empirical analysis, we present results using relative returns $A^m$ and one-factor risk adjusted returns $A^1$. A previous version of this paper, using the set of funds which survived to January 1999, reported results based on a five-factor alpha with market return, capitalization portfolio return, bond portfolio return, book-market portfolio return, and 'momentum' factor return. The results were very similar to what we report below, particularly with regard to the differential explanatory power of before-tax and after-tax returns. We focus our analysis on the simplest risk-adjustment strategy in part because the simplest relative return measure appears to be the strongest predictor of fund inflows.

The alternative risk-adjustment strategies have a limited impact on the relative ranking of funds by after-tax performance. Funds with extreme relative returns ($A^m$) also show extreme risk-adjusted returns ($A^1$). Of the 586 fund-years in the bottom decile of relative returns, 455 (78 percent) were in the bottom decile of one-factor adjusted returns, and another 100 (17 percent) were in the next decile. An additional 18 fund-years (3 percent) were in the next two deciles of the return distribution. At the top of the return distribution, the overlap is also striking. Of the 586 fund years in the top decile of relative returns, 95 percent of the fund-years were in the top two deciles of risk-adjusted returns.

It is conceptually more difficult to define an after-tax risk-adjusted portfolio performance measure than to define a pre-tax measure. We use the estimated $\beta$ from a one-factor pricing model estimated using pre-tax returns, the income tax rate, and the dividend distributions from the S&P 500 ($SP500_{inc}$) to construct an after-tax one-factor risk-adjusted return measure:

(4) $$A_a{}^1{}_{it} = R_{a,it} - (1 - \tau_d)*r_t - \beta^m{}_{it}*[(1 - \tau_d)*SP500_{inc} + (1 - \tau_{ucg})*SP500_{app} - (1 - \tau_d)*r_t].$$

$R_{a,it}$ is the after-tax return on fund i in year t, and we assume that capital gains on the S&P 500 ($SP500_{app}$) are taxed at our "effective accrual tax rate" on unrealized gains. This implicitly assumes that there are no current capital gain realizations associated with the market portfolio.

This measure of risk-adjusted after-tax fund performance is not completely satisfactory, since it takes a one-period approach to measuring the riskiness of a portfolio that will be held for many periods. In the taxable setting, unlike the no-tax environment, it is not possible to consider the riskiness of returns on a period-by-period basis, because the realization-based tax structure ties together after-tax returns in different periods.

### 3.3.3. Return persistence

For rational investors to adjust their mutual fund investments in response to historical differences in returns, past returns must help predict future performance. We therefore explore the degree of return persistence in our data set. We begin by estimating the degree of persistence of pretax and after-tax returns using our entire data sample. We estimate first-order autoregressions of the form

$$(5) \qquad R_{it} = \zeta_t + \rho * R_{it-1} + \upsilon_{it}$$

where $R_{it}$ denotes the return on fund i in year t, and $\zeta_t$ is a year-specific intercept term. We also estimate similar models for risk-adjusted returns, for after-tax returns, and for the tax burden on different funds.

Table 6 reports the resulting estimates. We find positive persistence across years for each of the measures of fund performance. For relative returns, the autocorrelation coefficient is 0.269 over the 1993-1998 period. The autocorrelation of the relative after-tax return is somewhat higher: 0.278 over this period. Perhaps more importantly for our analysis, there is substantial persistence in the estimated tax burden; the autocorrelation of $T_{it}$ is estimated at 0.265. This suggests that an investor who was concerned about minimizing the tax burden associated with a mutual fund investment could use past evidence on a fund's tax burden to predict the future burden of the fund. We interpret this as evidence of persistence in managerial styles. For example, fund managers who pursue low-turnover strategies are likely to generate relatively low tax burdens year after year.

The remaining panels of Table 6 show the autocorrelation of one-factor risk-adjusted return measures and the associated 'risk-adjusted tax burden.' These autocorrelations are greater than those of relative returns, i.e. returns that do not use a regression-based risk-adjustment strategy. With risk-adjusted returns, we find autocorrelations of pretax and after-tax returns of more than 0.29. The autocorrelation of the tax burden is estimated at 0.277. These findings support the notion that an investor could predict future tax burdens by studying the past performance of a mutual fund.

Our persistence estimates are significantly higher that those of Carhart (1997) and Gruber (1996), although Ippolito (1992) reports return autocorrelations that are similar to ours. It is difficult to compare our measures of return persistence to the measures in many other studies, since much of the previous literature has used measures of persistence of fund return across deciles of the return distribution, rather than autocorrelation coefficients. We suspect that our higher-than-usual autocorrelations are a result of the data sample that we are analyzing. The years 1993-1998 experienced persistently high equity returns, and there was persistence in the nature of these returns, with large capitalization growth stocks leading the market higher. The persistence of returns across sectors should generate persistence in the nature of returns for different funds, for example with growth-oriented large capitalization funds doing well year after year. Another factor that explains our high persistence values may be our relatively modest risk correction. Controlling for market capitalization, value/growth, and momentum effects reduces our estimates of the persistence of mutual fund returns.

### 3.4. The determinants of mutual fund tax burdens

The dispersion of tax burdens across mutual funds may contribute to differences in the net cash inflows to different funds, but it is also of interest in its own right. In this section, we explore the characteristics of mutual funds that are associated with high tax burdens. This analysis necessarily involves relating tax burdens to a set of variables, many of which are endogenous, and under the control of the fund manager. The rate at which the manager turns over the fund portfolio is a clear example. We do not attempt to develop a theory of why managers realize gains; Barclay, Pearson, and Weisbach (1998) have begun to explore this issue. We summarize the correlates of high tax burdens, and leave model building to future work.

We estimate partial correlation coefficients by fitting regression models of the form

$$T_{it} = \alpha + X_{it} * \beta + v_t + \zeta_{it} \tag{6}$$

where $T_{it}$ denotes our estimate of the tax burden on fund i in year t and $X_{it}$ is a set of fund characteristics. The set of explanatory regressors, $X_{it}$, includes: the turnover of stocks in the fund; an indicator variable for whether or not the fund is an index fund, which would indicate a reduced need for trading; an indicator for whether or not the fund is a tax-managed fund; and an indicator variable for new management taking charge of the fund in recent years, which may indicate a shift in portfolio strategy. We also include several years of lagged fund inflows as a share of fund assets, since a fund experiencing inflows does not need to sell shares to raise cash, and consequently has a greater opportunity to pursue a low realizations strategy. We also include the fund's current pretax returns, the fund's lagged tax burden, and a set of indicator variables for fund styles (large-cap growth, small-cap value, etc.), since realization differences across investment styles may influence investor tax burdens.

Table 7 reports two sets of regression results. In the first, all funds are assigned equal weight, while in the second, we weight each fund-year's observation the fund's total assets at the end of the previous year. We focus on the findings from the weighted regressions, since they describe the behavior of the average dollar invested in mutual funds. The results suggest several patterns. First, current and lagged turnover are both important correlates of a fund's tax burden. A twenty percentage point increase in annual turnover, from the mean of 79 percent to 99 percent, is associated with an 14 basis point increase in the fund's tax burden. While current turnover is associated with a higher tax burden, higher past turnover has a negative effect on the current tax burden. This is conditional on current turnover, and it presumably reflects the fact that assets that have been purchased recently are likely to have smaller embedded capital gains than assets that were purchased in the more distant past. As expected, the current tax burden is positively related to the share of a fund's value at the previous year-end that is comprised of unrealized appreciation on fund assets.

Our finding that current turnover is an important predictor of a fund's tax burden stands in contrast to some recent industry analyses, such as Belden (1998) and Barbee (1999), which suggest the opposite. This may be because we focus on the marginal impact of turnover in explaining tax burdens, rather than the total explanatory power of turnover in accounting for tax burden differences. In principle, turnover need not lead to higher tax burdens. A fund manager who realizes losses and holds gains may have a higher turnover rate than one who does not harvest losses, but the resulting tax burden on such a fund may be lower than that on a comparable, but lower-turnover, fund. Our empirical findings suggest that turnover is not typically directed at tax-minimization.

A number of other findings in Table 7 warrant comment. There is substantial positive serial correlation in the tax burdens on different funds. A ten basis point increase in the tax burden on a fund in the current year predicts between a one and two basis point increase in the tax burden next year. Index funds have substantially lower tax burdens than other funds. The average differential between the tax burden on index funds and other funds is roughly 45 basis points. The coefficient on the tax-managed fund indicator suggests that these funds also have tax burdens about 40 basis points below other funds. Managerial changes and past inflows are also correlated with current tax burdens. Funds with new managers have tax burdens about 40 basis points higher than other funds. Funds with higher inflows in previous years display lower tax burdens than funds with lower past inflows. Since inflows are persistent, funds with higher past inflows probably face a reduced need to sell securities to meet redemptions.

The information in Table 7 provides some background on the source of fund-to-fund differences in tax burdens. Many of the factors that we have used to "explain" fund tax burdens can be affected by fund managers. Chevalier and Ellison (1997) note that the compensation of such managers is highly dependent upon their assets under management. In this setting, the impact of tax burdens on a fund's asset base, which will be mediated through their effect on net inflows, becomes a central issue. This is the empirical question to which we now turn.

**3.5. Measuring mutual fund inflows**

To measure the net inflows to equity mutual funds, we rely primarily on data reported by Morningstar. We compute net inflows from annual data on fund assets. Morningstar reports total assets, as well as the net asset value (NAV) for each fund share, at the end of each calendar year. We estimate annual net inflows as a fraction of assets at the end of the previous year, $I^u_t$, as follows:

$$(7) \qquad I^u_t = Assets_t/Assets_{t-1} - (NAV_t + DIV_t + GAINS_t)/NAV_{t-1}.$$

This measure subtracts from the growth in fund size the portion attributable to returns on assets in the fund at the end of the previous year. It is the most commonly used measure of inflows in the empirical literature. We adjust this measure, following Ippolito (1992), to account for the fact that new shares are purchased throughout the year. We therefore compute a modified inflow measure ($I_t$) as:

$$(8) \qquad I_t = I^u_t/(1 + R_t/2)$$

where $R_t$ denotes the fund's return over the calendar year. In (7), $DIV_t$ and $GAINS_t$ correspond to dividend and capital gain distributions, respectively.

Our measure of net inflows distinguishes inflows that result from reinvestment of dividends and realized capital gains from net 'new money' inflows. (Net inflows including such reinvestments could be estimated as $I'_t = Assets_t/Assets_{t-1} - NAV_t/NAV_{t-1}$.) We focus on net 'new money' inflows to allow for the possibility that such inflows are more sensitive to relative performance than reinvested dividends and capital gains. Since roughly 90 percent of dividends and realized gains are reinvested at equity mutual funds, this seems like a plausible assumption. To explore the sensitivity of our findings to our assumption that 'new money' inflows are critical, we have estimated our basic regression equations using both $I'_t$ and $I^u_t$, rather than $I_t$, the dependent variable. The results are similar to the findings that we report using $I_t$.

One potential difficulty with estimating mutual fund net inflows from year-end information on fund assets deserves note. The cash inflow arising from the purchase of a share depends on the NAV at the time of the purchase. Measures of inflows such as (7) and (8), which are based on year-to-year changes in fund NAV and size, miss this within-year purchase timing effect. Especially when the return on a fund is a large positive or negative number, it is possible for the annual difference in assets under management to diverge from the actual inflows during the year. To evaluate the empirical importance of this bias, we obtained monthly data on fund net inflows for a small sample of equity mutual funds in the last few years of our sample period. The Financial Research Corporation provided these data. We then compared our estimate of the fund net inflow based on annual data with the actual sum of the monthly fund net inflows, and we found that the two estimates of net inflows diverged relatively little for most funds. Further detail on this calculation is presented in an earlier version of this paper.

The average fund in our sample experienced net inflows of 21.1 percent of beginning-of-year assets. Average inflows as a share of initial assets are smaller, 8.9 percent per year, when we weight funds by the initial asset value. This disparity suggests that on average larger funds experience smaller inflows, relative to assets, than smaller funds. Median net inflows are also smaller than mean net inflows. The median asset-weighted fund inflow is 3.5 percent. The difference between the mean and the median is indicative of substantial skewness in net inflow rates across funds. This is supported by summary statistics: the interquartile range for inflows as a share of initial assets was 38.8 percent (unweighted) and 20.5 percent (asset weighted). Forty-three percent of all fund-years in our sample showed net outflows rather than inflows. The wide differences in the inflow experience of different funds are the result of many factors. We now investigate whether differences in the tax burdens that funds place on their investors are one of them.

### 3.6. The determinants of mutual fund net inflows

The starting point for our analysis of mutual fund inflows is a regression model relating inflows to past returns and other fund characteristics:

$$I_{i,t} = R_{i,t-1}*\theta + X_{i,t}*\phi + v_t + \upsilon_{i,t}. \tag{9}$$

In this equation, $I_{i,t}$ is the fund's inflow, $R_{i,t-1}$ denotes a fund's past returns, possibly on a risk-adjusted basis and possibly for a period of several years, and the $X_{i,t}$ vector includes other factors that may explain fund inflows. We estimate models in which $R_{i,t-1}$ denotes lagged pretax returns, lagged after-tax returns, or both sets of returns, so that we can evaluate the relative predictive power of the two sets of return measures. Some of the variables included in $X_{i,t}$ are 'control variables' that may influence inflows for reasons unrelated to returns. These include fund age, the initial size of the fund, fund turnover, the fund's objective, and the fund's stock of unrealized capital gains.

The functional form linking past returns to current inflows has been an active subject of previous research. Sirri and Tufano (1998) and Chevalier and Ellison (1997) find substantial nonlinearities in this relationship: funds in the highest return strata experience large inflows relative to those with slightly lower returns. This suggests a 'stars effect' in fund inflows. We therefore present both ordinary least squares results from equation (9), in which lagged returns have a linear effect on fund inflows, as well as results from a specification that allows for different effects of returns on funds whose annual returns are in different quantiles of the return distribution. We also allow for a different derivative effect in the top five percentiles of each performance measure. Our findings about the relative importance of pre-tax and after-tax returns are relatively robust with respect to these changes of specification.

#### 3.6.1. Fund inflows and returns: results without other covariates

Table 8 presents the estimates from simple linear regressions that exclude any factors other than lagged returns from the equations explaining inflows. Table 9 presents analogous results based on spline regressions that allow for nonlinearity in the performance-inflow relationship. Each table presents results in which the explanatory variable, the fund return, is measured relative to the S&P 500 Index return. The tables also show results using fund returns that have been risk-adjusted using the one-factor risk adjustment procedure that we described above.

Each table includes results of regression models that are estimated weighting all funds equally, and that are estimated with observations on each fund weighted by fund assets. We report three regressions for each specification. The first simply relates fund inflows to lagged pretax returns, and the second relates inflows to both lagged pretax returns and the lagged tax burden. This provides a direct test of whether the tax burden has any explanatory power for fund inflows.

The results in Table 8 demonstrate the substantial explanatory power of lagged pretax returns in describing net mutual fund inflows. The return measure that we construct as the difference between a fund's return and the return on the S&P 500 has substantially more explanatory power than our one-factor risk-adjusted return. A one hundred basis point increase in a fund's return predicts between a two and a three percentage point increase in the fund's net inflows in the following year.

The findings in Table 8 are consistent with the view that some mutual fund investors are attuned to the tax burdens that their funds impose. When we include the tax burden in a regression model for net inflows, we clearly reject the null hypothesis that the tax burden does not affect such inflows. The findings suggest substantively important effects. A one hundred basis point increase in the tax burden on a fund is associated with between a four and an eight percentage point decrease in subsequent inflows. Thus a fund that moved from the 75$^{th}$ percentile to the 25$^{th}$ percentile in measured tax burden, which would correspond to a 0.8 percentage point change in tax burden, would experience an increased net inflow rate of between 3 and 7 percentage points.

One potential explanation of our findings is that index funds have grown rapidly during our sample period, and that they are relatively tax-efficient funds. To test this hypothesis, we excluded the Vanguard Index 500 fund from our regression sample. Since this fund accounts for a very large fraction of the total assets under indexed management, excluding it from the equations that are weighted by fund value removes most of the contribution of index funds to the estimates. The coefficient on the tax burden variable changes from -8.69 (0.85) to -8.86 (0.90) when we exclude the Vanguard Index 500, so this does not seem to be a key factor in our results.

Table 9 reports results similar to those in Table 8, except that the specification now allows for a nonlinear performance-inflow relationship. We use a spline function with five knots, at the 20$^{th}$, 40$^{th}$, 60$^{th}$, 80$^{th}$, and 95$^{th}$ percentiles of the pretax return distribution, to capture nonlinear effects. This specification allows different effects of returns on inflows at different parts of the return distribution. Our knot points are set based on the distribution of fund returns for the entire sample period. While this could lead to a high concentration of returns from one year in one quintile, this does not appear to happen.

Table 9 shows the effect of using the spline specification rather than the linear specification. Each of the coefficients indicates the marginal effect of returns for funds whose returns fall in particular parts of the return distribution. We present results using both pre-tax and after-tax returns, but we do not attempt to separately distinguish the effects of taxes and returns in these specifications.

The findings suggest substantial variation in the link between lagged returns and fund inflows at different points in this distribution. Like Sirri and Tufano's (1998) findings, the marginal effect of performance on net inflows is greater above the median of the return distribution than below the median. Consider the predicted difference in inflows between a fund that realizes and distributes capital gains of two percent of asset value, and a fund that distributes gains of five percent of asset value. Assume that the total return on the two funds is the same, so that the only effect of the difference in realizations is a difference in tax burden. Given our assumption about the tax rate on capital gains, the fund realizing gains of five percent would generate after-tax returns 60 basis points lower than those of the first fund. This return differential would result in a predicted inflow 3.3 percentage points smaller (using the relative return specification) or 2.5 percentage points smaller (using the risk-adjusted return specification) for the fund with the high tax burden.

The results in Tables 8 and 9 are based on data for the entire 1993-1998 sample period. There have been important changes during our sample period in the extent to which the tax consequences of mutual fund investing are discussed in the investment press. When Jeffrey and Arnott (1993) published their paper on investment returns for taxable clients, tax issues received much less attention than they do today. Morningstar now reports after-tax performance statistics for mutual funds, and popular magazines such as Business Week print data on after-tax returns. These developments suggest that investors may have become more sensitive to after-tax returns over time. To test this possibility, we estimated regression models like those in Table 8 with separate coefficients on the tax burden variable for each year. The negative effect of the tax burden on returns was greater in the last three years of the sample (1996, 1997, and 1998) than in the first two, although the year with the single largest effect of the tax burden is 1995. The time series of coefficient values nevertheless provides some support for the growing importance of tax-aware investing.

### 3.6.2. Fund characteristics, returns, and inflows

The foregoing regression models compare the predictive power of pretax and after-tax returns in forecasting mutual fund inflows, but they do not allow for any of the wide range of other attributes of individual mutual funds that might affect inflows. Other studies have allowed for a variety of such factors. Chevalier and Ellison (1997), for example, consider the age of a mutual fund and its size as potential determinants of fund inflows. Barclay, Pearson, and

Weisbach (1998) model fund growth rates as a function of lagged fund returns, a set of indicator variables for fund type, a measure of the fund expense ratio, front end load, and the funds' unrealized capital gains overhang. Their study is in many ways the closest antecedent to our work, and we try to include many of their control variables in our regression specifications. Their results are based on a data sample from the 1976-1992 period, while our results are for a separate and more recent period. There have also been changes over time in marginal tax rates and in the relative importance of taxable and tax-exempt (retirement account) investors in the mutual fund market. Despite these changes, our findings about the relationship between fund inflows and lagged returns are broadly consistent with the findings in Barclay, Pearson, and Weisbach (1998).

We add control variables to our regression models for fund inflows for two reasons. First, it is possible that pretax and after-tax returns are correlated with these other fund attributes in ways that lead to spurious conclusions about how returns affect inflows. Second, some variables other than lagged pretax and post-tax return, particularly the fund's capital gains overhang, are of independent interest for analyzing how taxation affects the behavior of mutual fund investors.

We expand our basic regression specification by including the following covariates: age of the fund, which we specify as two indicator variables, one for funds that are between three and eight years old, and another for funds that are older; fund size, which is measured in logarithms and has proven to be an important predictor of inflows in previous studies; the fund's expense ratio in the previous year; an indicator variable for whether the fund has a load; and the lagged fund inflow, to allow for persistence in fund flows. We also include a set of indicator variables for eight types of equity mutual funds, to capture differences across funds that are related to investment style. We also include the median market capitalization and average price/book ratio of the stocks in each fund's portfolio as an additional measure of the fund's investment strategy. Finally, we include the Morningstar 'rating' assigned to a fund; these ratings are widely quoted and may significantly affect net inflows.

To avoid presenting an unwieldy number of regressions, we limit our focus in two ways. First, we concentrate on models in which lagged returns and tax burdens have a linear effect on inflows. Since the spline specifications in Table 9 generated results that were broadly similar to those from the linear specification, this restriction does not seem likely to affect our central conclusions. Second, we limit our analysis to the simplest measure of risk-adjusted returns, the one that subtracts the return on the S&P 500 from the return on each equity mutual fund. Since this return measure had the highest explanatory power in the earlier specifications, and since our findings about the importance of the tax burden variable were relatively insensitive to our choice of the risk-adjustment algorithm, this restriction again should not affect our conclusions.

Tables 10 and 11 report the central findings from our expanded specification. Some of the new covariates have substantial effects on fund inflows, and adding the controls improves the explanatory power of the regression model, but the central results on the difference between pre- and post-tax returns are not affected by adding the controls. The results continue to suggest that funds with higher tax burdens experience lower inflows than similar funds with lower tax burdens.

A number of the control variables have effects that are of interest in their own right. The findings suggest that inflows are greater at younger funds, and that the proportional inflow of assets is smaller at large funds. The coefficients on the objective variables indicate that, controlling for fund performance, inflows to 'small company' funds have been greater than inflows to other types of domestic equity funds. The coefficients on the expense ratio variable are negative but statistically insignificant, and the coefficient on the turnover variable provides weak evidence that investors prefer funds with less turnover. The Morningstar 'rating' is on a 5-point scale; increasing the rating by a point raises by about 10 percentage points the expected value of net inflows.

If taxable investors are concerned about purchasing shares in a fund that might realize gains and thereby burden them with higher taxes, a larger unrealized capital gain could be associated with smaller fund inflows. Barclay, Pearson, and Weisbach (1998) presented results confirming this prediction. Columns 3 and 4 of Tables 10 and 11 report results of inflow equations that include the capital gains overhang variable. The results support the view that capital gains overhang is a statistically significant determinant of fund inflows. The weighted results imply that a ten percent increase in the share of unrealized capital gains relative to fund assets is associated with a reduction of between 2 and 5 percentage points in fund inflows.

### 3.6.3. Alternative approaches to capital gains

The foregoing results are based on a measure of tax burden that aggregates long-term and short-term capital gains, and that assumes that any short-term gains are taxed at the long-term capital gains tax rate. While we cannot disaggregate the components of capital gain realizations for funds that have disappeared, we can use the sample of funds in the January 1999 Morningstar data release to assess possible biases from aggregating capital gains.

Table 12 presents coefficient estimates from models like those in Table 11. The estimates in the first column use a tax-burden measure that aggregates capital gains components, just like the estimates in Table 11, while the results in the second column use a tax burden measure that disaggregates these components and applies the income tax rate to the short-term component of capital gains. The sample period for the results in Table 12 is smaller than that for the results in Table 11, and the standard errors for the coefficients are correspondingly larger.

The results in Table 12 suggest that the coefficient estimates for the tax burdens in Tables 10 and 11 may be biased away from zero. Disaggregating capital gain realizations into short-term and long-term components and applying the higher income tax rate to the short-term component changes the estimated tax burden coefficient from –4.46 to –3.69. The large standard error associated with this coefficient estimate, 0.79, makes it difficult to draw any definitive conclusion from this result. The findings in Table 12 are encouraging, since they suggest that the basic pattern of results that we find using an aggregated measure of capital gain realizations still emerges when we use the disaggregate data on capital gains.

A separate measurement issue that warrants some investigation is our treatment of the accrual equivalent tax rate on accruing but unrealized capital gains. For most of the funds in our sample, undistributed capital gains account for at least half of the pretax return. Until now, we have assumed that the accrual equivalent tax burden on these gains is 10 percent, half the statutory long-term capital gains tax rate in 1998. Most previous research on the taxation of fund returns assumes that undistributed capital gains are effectively untaxed.

To explore the sensitivity of our findings to our assumption about the tax burden on unrealized gains, we estimated regression models like those in Table 11, but with different assumptions about the tax burden on unrealized gains. Table 13 reports our findings. The tax burden measure in the first column assumes that the effective tax rate on accruing capital gains is 10 percent, while the second column assumes that accruing unrealized gains are untaxed. Varying the effective tax rate on undistributed gains has a large effect on the estimated coefficient, but there is almost no effect on this coefficient's statistical significance. Reducing the effective tax rate from 10 percent to zero changes the t-statistic of the tax burden coefficient from 4.79 to 4.75. These results suggest that the broad picture that emerges from our empirical analysis is unaffected by our assumption about the effective tax rate on a fund's accruing gains.

### 3.6.4. The effect of tax burdens on inflows to "institutional" funds

Our empirical findings for a large sample of retail funds are consistent with the hypothesis that taxable investors are allocating their money across funds in part in response to difference in the fund's after-tax returns. It is nevertheless possible that these results are not driven by the behavior of tax-conscious individual investors seeking to avoid tax liabilities, but by other factors. The tax burden on funds that generate returns in the form of capital gains, particularly unrealized capital gains, is lower than the tax burden on funds that generate more of their income from dividends. If investors "chase" capital gains, then inflows could exhibit the pattern that we find even if investors are not concerned about the after-tax performance of their funds. More generally, given the limited attention that the tax status of various funds received until the middle of our sample period, there is some question of whether tax-aware mutual fund investing is the best explanation for our findings.

One way to evaluate this question is to study the relationship between lagged returns, and lagged tax burdens, and fund inflows for a set of funds that is unlikely to be held by taxable investors. We do this by studying inflows to institutional mutual funds. Most institutional investors, such as pension funds and endowments, are not taxable, so they should be concerned with pretax rather than after-tax returns. Morningstar identifies some funds as "institutional," but there is substantial heterogeneity within this group. Funds may be included in this category because they have large minimum balance requirements, or because they restrict the set of investors who may purchase funds.

We identified a sample of 751 fund-years corresponding to 'institutional' funds over the 1993-1998 period, and we estimated our basic regression models with these data. Table 14 presents our findings, which provide only mixed support for our "taxable investor" interpretation. For the set of institutional funds, there is a strong positive effect of pretax returns on net inflows, and a negative effect of the fund's tax burden. The coefficient on the pretax return in the linear specification is 2.74 (0.49), compared with 1.90 (0.16) in our sample of retail funds. The coefficient on the tax burden for the institutional funds is –5.97 (1.66), compared with –3.79 (0.79) for the noninstitutional funds. This negative coefficient on the tax burden variable, for a set of funds that is unlikely to be held by taxable investors, is a substantial challenge to the "tax aware" interpretation of the earlier results. We do not have a convincing explanation at this stage of what accounts for this finding; we are continuing to explore various possibilities. It may be that even institutional funds are held in substantial part by taxable investors, and that their behavior accounts for enough of the variation in inflows to institutional funds to generate results like those for non-institutional funds. Some investment-management firms, for example, may offer private clients the opportunity to invest through institutional funds. These clients may be among the <u>most</u> tax-conscious in the mutual fund marketplace.

A different finding from the institutional fund sample is supportive of the view that investors in retail funds consider taxes in their investment decisions. For the institutional fund sample in Table 14, there is no evidence that capital gains overhangs discourage inflows. The coefficient on the capital gains overhang variable is four times larger for the retail funds than for the institutional funds.

### 3.7. Gross inflows and gross outflows

The data from Morningstar and most other sources make it possible to construct net inflows, but not gross purchases and gross sales, at individual mutual funds. As a result, most previous research, with prominent exception of Chordia's (1996) study of the relationships among redemptions, load charges, and fund cash balances, has analyzed the determinants of net inflows. The Investment Company Institute (1999) presents aggregate evidence showing that net inflows are the result of large, and in part offsetting, gross inflows and gross redemptions. In recent years gross redemptions for equity, bond, and hybrid funds have been just under 20 percent of total assets.

There may be important differences in the way an individual fund's return history and other characteristics affect gross inflows and gross redemptions. To explore these issues, we collected gross inflow and gross outflow data for a small subset of funds. We identified the 200 largest mutual funds in our sample in each of the past five years, and searched the SEC's EDGAR archive (at www.sec.gov), the private edgar-online page (www.edgar-online.com), and fund web pages themselves for reports detailing these funds' share purchases and redemptions. The resulting dataset contains 686 fund-years of data over the period 1994-1998. Limiting our sample in this way avoids explicit conditioning on mutual funds' subsequent growth, except to the extent that this growth affects our ability to gather fund data.

Table 15 reports summary measures based on these data. For all 686 fund-years, the gross inflow averages 36.6 percent of beginning-of-year assets, while the average gross outflow amounts to 30.5 percent of assets. The flows are somewhat smaller, an inflow of 36.1 percent and an outflow of 26.5 percent, when we weight funds by their total assets under management. The outflows are <u>not</u> the result of investors taking distributions of dividends or realized gains. The average reinvestment rate for firms in our 1998 sample was over 93 percent, and the minimum was 81 percent. Thus these statistics suggest that the net inflow measures that we have analyzed prior to this point mask much larger gross inflows and gross outflows.

If taxable investors observe persistence in tax-management skills and allocate new investment according to after-tax performance, then we should find a strong effect of lagged returns on gross inflows. Alternatively, if investors are reluctant to sell shares of funds that have accrued substantial undistributed capital gains, which are typically "tax efficient" funds, then we might find a positive relationship between measured tax burdens and subsequent gross outflows. Both explanations could yield a negative link between net inflows and tax burdens, but they cannot be distinguished without data on gross flows.

Table 16 reports regression results in which the dependent variables are the net inflow (column 1), the gross inflow (column 2) and the gross outflow (column 3) for each fund in our restricted sample. The equations in the first part of each panel do not include the capital gains overhang variable, while those in the second part of each panel do. In addition, we have divided the results into Panel A and Panel B, corresponding to unweighted and weighted results. The independent variables in all equations are the lagged relative return, the lagged relative tax burden, and a full set of year dummies. In Panel A, the first column shows that the effect of pretax returns and tax burdens is similar in this restricted sample and in the much larger Morningstar sample that we used above. The pretax return has a positive effect on net inflows, and the tax burden has a negative effect. The second and third columns present results that disaggregate these effects. Most of the effect of pretax returns on net inflows is due to a strong effect of pretax returns on gross inflows. The effect of pretax returns on gross outflows is minimal.

High tax burdens are associated both with lower gross inflows and lower gross outflows. The effect of tax burdens on net inflows is negative and significant, as we would expect if taxable investors were allocating their new money to mutual funds in part based on past after-tax returns. Past tax burdens have a negative effect on outflows, although this effect is never statistically significant.

The results in Table 16 with respect to the interaction between gross flows and the undistributed capital gains overhang also confirm our earlier results using the Morningstar sample. A high capital gains overhang significantly reduces net inflows to a fund. This is the result of a large negative effect on gross inflows, and an offsetting (but weaker) negative effect on gross outflows. The gross inflow effect is consistent with taxable investors trying to avoid funds that will accelerate the distribution of capital gains. It provides additional support for Khorana and Servaes' (1999) finding that new funds are more likely to be created in parts of the mutual fund marketplace that are occupied by established funds with substantial capital gains overhangs. The gross outflow effect is consistent with taxable investors being reluctant to sell shares in, and realize gains in, funds that have large embedded capital gains. These results are generally supportive of the view that fund flows respond to factors that taxable investors would consider in determining their fund allocations. The value of the gross flows data is clearly illustrated by the interesting findings with respect to gross redemptions, which could not be detected using only information on net fund flows.

### 3.8. Conclusion

This paper suggests that the individual income tax burden that fund investors face when they hold a fund is negatively correlated with fund inflows. This is consistent with the view that taxable investors consider the impact of income taxation on asset returns when they decide which mutual fund shares to purchase or redeem. Mutual funds that offer higher after-tax rates of return attract greater inflows than those with lower after-tax returns, even after we control for a fund's pretax return. We also find that a fund's unrealized capital gain "overhang" negatively affects net fund inflows, even though it also reduces the likelihood of redemptions. This result is consistent with Barclay, Pearson, and Weisbach's (1998) findings for an earlier data sample. While the inflow effects associated with changes in income tax burdens or capital gains overhang are modest, they are comparable in magnitude to the effects of fund expense ratios on inflows.

Our findings suggest that taxation may play a role in the way investors choose their mutual funds. Yet there are several reasons for caution in interpreting the results. One is that for part of our sample period, particularly the early years, investors would have to work hard to obtain information on a fund's after-tax returns. The barriers to information acquisition have fallen in recent years, and the apparent impact of tax burden on fund inflows has increased. The concern that investors might not be aware of fund tax circumstances also applies to our findings, and perhaps even more to findings based on earlier sample periods, with respect to the impact of unrealized gains on fund inflows.

A second concern is that a substantial share of the assets at mutual funds, roughly 35 percent at year-end 1998, and a much higher share in some large equity funds, is held in tax-deferred retirement accounts. Investors holding funds in these accounts should not be sensitive to the tax burden measures that we study. Ideally, we would like to measure the fund inflows that are attributable to taxable individual investors, and to study how those flows respond to various factors. We are not aware of any data source that provides the requisite information on fund flows, however. The simple existence of a substantial body of non-taxable money in equity mutual funds is not inconsistent with our findings. It does, however, imply that taxable investors are even more sensitive to tax burdens than our results otherwise suggest.

A third concern emerges from our findings with respect to institutional rather than retail mutual funds. Since institutional funds are less likely to attract taxable investors than their retail counterparts, one would expect a smaller impact of tax variables on inflows to such funds. Our results confirm this with respect to the impact of the capital gains overhang variable, but not with respect to the impact of the tax burden on fund returns.

There are other puzzles associated with mutual fund flows and the importance of taxable investors. One is the relatively slow growth of "tax efficient" mutual funds in the mid-1990s. A number of major mutual fund complexes, including Vanguard and Charles Schwab, have introduced funds that are targeted to taxable investors who are concerned about capital gain realizations. These funds also try to reduce their dividend income relative to capital gains. While these funds have grown more rapidly than other mutual funds since they were introduced, they still represent a small share of the mutual fund marketplace. In 1998 (1996), tax-managed funds accounted for 0.4 percent (0.14 percent) of the assets of the equity mutual funds in our sample. If flows to existing mutual funds are sensitive to the tax burden on these funds returns, one would have expected greater growth of tax-efficient mutual funds. One response to this concern is that index funds have grown rapidly during the last decade, and most index funds represent relatively tax-efficient investment vehicles.

Finally, the general growth of mutual funds as vehicles for taxable investors to hold common stocks raises fundamental questions about the degree to which taxes affect investor behavior. Because mutual funds cede decisions about realizing gains and losses from the individual investor to a mutual fund manager, they reduce the individual's control over portfolio decisions with substantial tax consequences. Mutual fund investing may offer other advantages that offset the potential increase in investor tax burdens, such as the opportunity to diversify portfolio holdings. Studying the determinants of investor choices between common stocks and mutual funds is a natural issue for further investigation.

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Table 1. Ownership of Taxable Mutual Funds, 1998

| Household Income Category | Total Number of Households Owning Taxable Mutual Funds | Total Holdings of Taxable Mutual Funds |
|---|---|---|
| < $50,000 | 5.94 million (36.7 percent) | 210 billion (14.3 percent) |
| $50-100,000 | 6.40 (39.5) | 434 (29.6) |
| $100-150,000 | 1.79 (11.1) | 158 (10.8) |
| $150-250,000 | 1.19 (7.3) | 205 (14.0) |
| > $250,000 | 0.88 (5.4) | 460 (31.3) |
| Total | 16.20 (100.0) | 1467 (100.0) |

Source: Authors' tabulations from 1998 Survey of Consumer Finances. Entries in parentheses are percentages of column totals. Returns are measured net of expenses.

Table 2. Summary Statistics on Mutual Fund Returns, 1993-1998 (5866 fund years)

| Return Component | Mean | Median | Interquartile Range |
|---|---|---|---|
| Pretax Return | 17.1 | 18.5 | 18.0 |
| Dividend Yield | 1.0 | 0.6 | 1.6 |
| Capital Gain Distributions | 8.3 | 7.1 | 8.9 |
| Undistributed Capital Gain | 7.8 | 7.9 | 18.3 |
| Tax Burden | 3.0 | 3.2 | 2.4 |
| After-Tax Return | 14.1 | 15.1 | 16.1 |
| Taxes/Pretax Return (Conditional on Pretax Return > 0) | 18.4 | 16.0 | 7.9 |

Source: Authors' calculations using Morningstar Principia databases.

Table 3. Mean Pre-tax and After-Tax Returns, by Years, 1993-1998

| | | Fund-Weighted | | Asset-Weighted | |
|---|---|---|---|---|---|
| Year | Sample Size | Pretax Return | Tax Burden | Pretax Return | Tax Burden |
| 1993 | 509 | 12.7 | 2.7 | 13.8 | 2.8 |
| 1994 | 644 | -1.8 | 0.9 | -0.7 | 1.1 |
| 1995 | 773 | 30.5 | 4.7 | 32.6 | 4.9 |
| 1996 | 1003 | 18.1 | 3.7 | 18.1 | 3.5 |
| 1997 | 1330 | 23.4 | 3.7 | 25.7 | 3.8 |
| 1998 | 1607 | 13.9 | 2.2 | 20.9 | 3.0 |
| All Years | 5866 | 17.1 | 3.0 | 20.9 | 3.4 |

Notes: Authors' tabulations using data from Morningstar 1994-1999 databases. Tax burden calculations assume a marginal tax rate of 31 percent on dividends, the statutory maximum long-term capital gains tax rate on capital gains distributions, and an effective tax rate of 10 percent on undistributed capital gains.

Table 4. Pretax Returns, After-tax Returns, and Embedded Capital Gains: 20 Largest Equity Mutual Funds, 1998

| Fund Name | Assets ($B) | Pretax Return | Undistributed Appreciation | Dividends | Realized Capital Gains | Tax Burden | After-Tax Return | Unrealized Capital Gains/ Asset Value |
|---|---|---|---|---|---|---|---|---|
| Fidelity Magellan* | 83.6 | 32.9 | 26.8 | 0.7 | 5.4 | 4.0 | 28.9 | 44% |
| Vanguard Index 500 | 69.5 | 28.5 | 26.5 | 1.5 | 0.5 | 3.2 | 25.2 | 46% |
| Washington Mutual Investors | 51.8 | 19.0 | 8.4 | 2.0 | 8.6 | 3.2 | 15.8 | 35% |
| Investment Company of America | 48.5 | 22.2 | 10.0 | 1.8 | 10.4 | 3.6 | 18.6 | 42% |
| Vanguard Windsor II | 30.9 | 15.9 | 4.4 | 2.2 | 9.3 | 3.1 | 12.7 | 27% |
| American Century/ 20th Century Ultra | 27.2 | 33.8 | 22.4 | 0.0 | 11.4 | 4.5 | 29.3 | 31% |
| Janus | 25.5 | 38.8 | 35.2 | 0.3 | 3.3 | 4.3 | 34.5 | 26% |
| Fidelity Advisors Growth Opportunity | 24.8 | 23.6 | 18.4 | 0.8 | 4.4 | 3.0 | 20.6 | 33% |
| Fidelity Equity-Income | 23.7 | 12.2 | 6.0 | 1.6 | 4.6 | 2.0 | 10.1 | 36% |
| Putnam Growth & Income A | 20.3 | 14.9 | 4.8 | 2.4 | 7.7 | 2.8 | 12.2 | 19% |
| Fidelity Blue-Chip Growth | 19.9 | 33.2 | 27.7 | 0.3 | 5.2 | 4.0 | 29.2 | 37% |
| Fidelity Equity-Income II | 19.5 | 22.1 | 11.1 | 1.2 | 9.8 | 3.5 | 18.7 | 35% |
| MSDW Dividend Growth Securities | 18.5 | 17.6 | 12.9 | 1.4 | 3.3 | 2.4 | 15.2 | 53% |
| Growth Fund of America | 16.2 | 31.5 | 19.2 | 0.5 | 11.8 | 4.4 | 27.1 | 44% |
| Putnam Growth & Income B | 16.1 | 14.2 | 4.8 | 1.6 | 7.8 | 2.5 | 11.6 | 20% |
| Janus Twenty | 15.8 | 73.4 | 71.9 | 0.5 | 1.0 | 7.5 | 65.9 | 39% |
| AIM Constellation A | 14.3 | 18.6 | 15.7 | 0.0 | 2.9 | 2.2 | 16.5 | 38% |
| Putnam Voyager A | 13.9 | 23.4 | 15.1 | 0.0 | 8.3 | 3.2 | 20.2 | 37% |
| T Rowe Price Equity-Income | 13.5 | 9.0 | 1.0 | 2.3 | 5.7 | 2.1 | 6.9 | 24% |
| Fundamental Investors | 12.7 | 16.5 | 5.5 | 1.5 | 9.5 | 2.9 | 13.6 | 25% |
| Vanguard US Growth | 12.3 | 39.3 | 30.6 | 0.7 | 8.0 | 5.1 | 34.3 | 44% |

Note: Authors' tabulations based on Morningstar Principia Database. Tax burden calculations assume a marginal tax rate of 31 percent on dividends, the statutory maximum long-term capital gains tax rate on capital gains distributions, and an effective tax rate of 10 percent on undistributed capital gains. The Fidelity Magellan Fund, closed as of the end of 1998 (though now reopened), is not in our sample in that year.

Table 5. Pretax Returns, After-tax Returns, and Embedded Capital Gains: 20 Largest S&P 500 Index Mutual Funds, 1998

| Fund Name | Assets ($B) | Pretax Return | Undistributed Appreciation | Divi-dends | Realized Capital Gains | Tax Burden | After-Tax Return | Unrealized Capital Gains/ Asset Value |
|---|---|---|---|---|---|---|---|---|
| Vanguard Index 500 | 69.54 | 28.5 | 26.5 | 1.5 | 0.5 | 3.2 | 25.2 | 46% |
| Fidelity Spartan Market Index | 7.15 | 28.1 | 24.4 | 1.2 | 2.5 | 3.3 | 24.8 | 30% |
| T. Rowe Price Equity Index | 3.35 | 28.2 | 26.6 | 1.3 | 0.3 | 3.1 | 25.0 | 36% |
| S Sg A S&P 500 Index | 2.25 | 26.3 | 12.3 | 1.6 | 12.4 | 5.5 | 20.8 | 28% |
| Dreyfus S&P 500 Index | 2.15 | 28.1 | 26.8 | 1.3 | 0.0 | 3.1 | 25.0 | 38% |
| BT Investment Equity 500 Index | 0.87 | 28.3 | 24.8 | 1.5 | 2.0 | 3.3 | 25.0 | 54% |
| MainStay Equity Index A | 0.80 | 27.6 | 25.5 | 0.7 | 1.4 | 3.1 | 24.6 | 38% |
| Galaxy II Large Company Index Retail | 0.75 | 28.0 | 25.3 | 1.3 | 1.4 | 3.2 | 24.8 | 43% |
| Victory Stock Index | 0.71 | 26.4 | 13.6 | 1.9 | 10.9 | 4.2 | 22.2 | 21% |
| Stagecoach Equity Index A | 0.61 | 27.4 | 21.0 | 1.0 | 5.4 | 3.5 | 23.9 | 70% |
| OneGroup Equity Index B | 0.41 | 26.5 | 22.2 | 0.3 | 4.0 | 3.1 | 23.4 | 36% |
| Pegasus Equity Index A | 0.32 | 27.5 | 18.9 | 0.9 | 7.7 | 3.7 | 23.8 | 37% |
| OneGroup Equity Index A | 0.27 | 27.4 | 22.3 | 1.1 | 4.0 | 3.4 | 24.0 | 34% |
| Munder Index 500 A | 0.25 | 27.8 | 25.4 | 1.3 | 1.1 | 3.2 | 24.6 | 35% |
| Wachovia Equity Index A | 0.14 | 27.6 | 24.3 | 1.3 | 2.0 | 3.3 | 24.3 | 31% |
| Firstar Equity Index Retail | 0.13 | 28.3 | 26.3 | 1.3 | 0.7 | 3.2 | 25.1 | 50% |
| California Investment S&P 500 Index | 0.13 | 28.3 | 23.8 | 1.8 | 2.7 | 3.5 | 24.8 | 39% |
| First American Equity Idx A | 0.07 | 28.0 | 24.6 | 1.2 | 2.2 | 3.3 | 24.7 | 36% |
| First American Equity Idx B | 0.06 | 27.1 | 24.4 | 0.4 | 2.3 | 3.0 | 24.0 | 39% |
| Black Rock Index Equity Investors A | 0.05 | 27.9 | 26.9 | 0.7 | 0.3 | 3.0 | 24.9 | 38% |

Note: Authors' tabulations based on Morningstar Principia Database. Tax burden calculations assume a marginal tax rate of 31 percent on dividends, the statutory maximum long-term capital gains tax rate on capital gains distributions, and an effective tax rate of 10 percent on undistributed capital gains.

Table 6. Linear Regressions for Persistence of Mutual Fund Returns, Pre-tax and Post-tax Basis

| | Relative Return Measures | | | One-Factor Risk-Adjusted Return Measures | | |
|---|---|---|---|---|---|---|
| | Pretax | After-Tax | Tax Burden | Pretax | After-Tax | Tax Burden |
| Unweighted Results | | | | | | |
| Lagged | 0.269 | 0.278 | 0.265 | 0.296 | 0.298 | 0.277 |
| Return | (0.017) | (0.017) | (0.014) | (0.016) | (0.016) | (0.016) |
| R2 | 0.211 | 0.262 | 0.406 | 0.140 | 0.133 | 0.199 |
| Results Weighting Funds by Net Assets | | | | | | |
| Lagged | 0.367 | 0.369 | 0.389 | 0.404 | 0.396 | 0.427 |
| Return | (0.019) | (0.019) | (0.015) | (0.018) | (0.018) | (0.016) |
| R2 | 0.153 | 0.209 | 0.503 | 0.123 | 0.117 | 0.220 |

Notes: Estimates based on relative return measures use 5866 fund-year observations; estimates based on risk-adjusted return measures use 4389 fund-year observations. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 7. Regression Estimates of the Determinants of Mutual Fund Tax Burdens

| Variable | Mean | Unweighted | | | Asset-Weighted | | |
|---|---|---|---|---|---|---|---|
| Constant | | 1.014 | 1.352 | 1.075 | 1.257 | 1.513 | 1.112 |
| | | (0.122) | (0.114) | (0.127) | (0.192) | (0.154) | (0.196) |
| Tax Burden | 3.224 | 0.211 | 0.245 | 0.189 | 0.200 | 0.181 | 0.145 |
| Year t-1 | | (0.020) | (0.028) | (0.021) | (0.040) | (0.035) | (0.038) |
| Tax Burden | 2.908 | 0.122 | 0.092 | 0.112 | 0.137 | 0.088 | 0.097 |
| Year t-2 | | (0.022) | (0.019) | (0.021) | (0.043) | (0.036) | (0.037) |
| Turnover | 0.790 | 0.431 | 0.448 | 0.448 | 0.692 | 0.745 | 0.753 |
| | | (0.053) | (0.058) | (0.054) | (0.115) | (0.110) | (0.113) |
| Lagged | 0.801 | -0.268 | -0.289 | -0.244 | -0.472 | -0.471 | -0.438 |
| Turnover | | (0.043) | (0.043) | (0.044) | (0.096) | (0.090) | (0.092) |
| Return | 18.079 | 0.113 | 0.117 | 0.114 | 0.106 | 0.110 | 0.110 |
| Year t | | (0.020) | (0.002) | (0.020 | (0.029) | (0.003) | (0.030) |
| Return | 16.818 | -0.034 | -0.035 | -0.032 | -0.018 | -0.016 | -0.015 |
| Year t-1 | | (0.003) | (0.004) | (0.004) | (0.008) | (0.007) | (0.007) |
| Return | 14.715 | -0.026 | -0.018 | -0.026 | -0.031 | -0.021 | -0.028 |
| Year t-2 | | (0.004) | (0.003) | (0.004) | (0.007) | (0.005) | (0.007) |
| New Manager | 0.060 | 0.243 | 0.283 | 0.263 | 0.453 | 0.439 | 0.438 |
| This Year? | | (0.079) | (0.079) | (0.078) | (0.160) | (0.158) | (0.147) |
| New Manager | 0.096 | 0.124 | 0.161 | 0.145 | 0.011 | 0.050 | 0.045 |
| Last Year? | | (0.061) | (0.060) | (0.061) | (0.085) | (0.076) | (0.079) |
| Expense Ratio | 1.272 | -0.061 | -0.101 | -0.083 | -0.017 | -0.080 | -0.079 |
| | | (0.062) | (0.059) | (0.068) | (0.071) | (0.050) | (0.052) |
| 8<= Fund Age < | 0.354 | -0.032 | -0.048 | -0.060 | -0.137 | -0.165 | -0.171 |
| 16 | | (0.040) | (0.036) | (0.040) | (0.056) | (0.056) | (0.060) |
| 16<= Fund Age | 0.313 | -0.006 | 0.021 | -0.014 | 0.023 | -0.003 | -0.014 |
| | | (0.044) | (0.042) | (0.045) | (0.061) | (0.058) | (0.065) |
| Index Fund | 0.032 | | -0.312 | -0.331 | | -0.469 | -0.457 |
| Indicator | | | (0.076) | (0.079) | | (0.114) | (0.119) |
| Tax-Managed | 0.001 | | -0.742 | -0.750 | | -0.382 | -0.428 |
| Indicator | | | (0.071) | (0.072) | | (0.110) | (0.119) |
| Inflows at t-1 | 18.769 | -0.139 | -0.165 | -0.138 | -0.321 | -0.311 | -0.268 |
| (x $10^{-2}$) | | (0.029) | (0.029) | (0.030) | (0.061) | (0.051) | (0.053) |
| Inflows at t-2 | 27.635 | -0.015 | -0.021 | -0.014 | 0.023 | -0.028 | -0.004 |
| (x $10^{-2}$) | | (0.020) | (0.021) | (0.021) | (0.038) | (0.034) | (0.035) |
| Inflows at t-3 | 48.634 | -0.024 | -0.022 | -0.025 | -0.025 | -0.025 | -0.030 |
| (x $10^{-2}$) | | (0.013) | (0.014) | (0.013) | (0.016) | (0.016) | (0.016) |
| Unrealized | 20.710 | 0.006 | | 0.008 | 0.002 | | 0.006 |
| Gains (t-1) | | (0.002) | | (0.002) | (0.003 | | (0.003) |
| Fund Style | | No | Yes | Yes | No | Yes | Yes |
| Indicators? | | | | | | | |
| R2 | | 0.815 | 0.804 | 0.819 | 0.871 | 0.872 | 0.879 |
| N | | 2752 | 3313 | 2752 | 2752 | 3313 | 2752 |

Notes: All estimates are based on 2752 fund-year observations for the period 1993-1998. All equations include indicator variables for each year, as well as indicator variables for fund styles. Standard errors, shown in parentheses, are corrected for clustering.

Table 8. Linear Models for Mutual Fund Inflows and Return Measures

| Variable (lag) | Returns Relative to S&P 500 | | | One-Factor Risk-Adjusted Returns | | |
|---|---|---|---|---|---|---|
| Unweighted | | | | | | |
| Pretax Return | 2.918 | | 3.548 | 1.608 | | 2.005 |
| | (0.192) | | (0.226) | (0.130) | | (0.161) |
| After-tax Return | | 3.334 | | | 1.805 | |
| | | (0.211) | | | (0.142) | |
| Tax Burden | | | -5.526 | | | -4.114 |
| | | | (1.232) | | | (1.102) |
| R2 | 0.106 | 0.110 | 0.111 | 0.072 | 0.075 | 0.076 |
| Results Weighted by Fund Net Assets | | | | | | |
| Pretax Return | 2.060 | | 2.963 | 1.189 | | 1.993 |
| | (0.111) | | (0.166) | (0.083) | | (0.136) |
| After-tax Return | | 2.415 | | | 1.390 | |
| | | (0.127) | | | (0.093) | |
| Tax Burden | | | -8.691 | | | -8.267 |
| | | | (0.849) | | | (0.999) |
| R2 | 0.176 | 0.197 | 0.219 | 0.117 | 0.131 | 0.161 |

Notes: Estimates based on relative return measures use 5866 fund-year observations; estimates based on risk-adjusted return measures use 4389 fund-year observations. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 9. Mutual Fund Inflows and Return Measures - Spline Regressions

| Variable | Returns Relative to S&P 500 | | | One-Factor Risk-Adjusted Returns | | |
|---|---|---|---|---|---|---|
| Unweighted<br>Lagged Return<br>Percentiles: | Pretax | After-tax | Pretax | Pretax | After-tax | Pretax |
| < 20 | 1.242 | 1.453 | 1.873 | 0.694 | 0.897 | 1.068 |
| | (0.280) | (0.263) | (0.305) | (0.159) | (0.179) | (0.177) |
| $20^{th}$-$40^{th}$ | 0.882 | 1.963 | 1.438 | 0.960 | 0.094 | 1.318 |
| | (0.537) | (0.608) | (0.547) | (0.702) | (0.782) | (0.688) |
| $40^{th}$-$60^{th}$ | 6.330 | 6.613 | 6.899 | 4.144 | 5.565 | 4.340 |
| | (0.891) | (1.024) | (0.904) | (1.285) | (1.336) | (1.289) |
| $60^{th}$-$80^{th}$ | 4.000 | 4.151 | 4.366 | 3.105 | 3.251 | 3.417 |
| | (1.215) | (1.212) | (1.211) | (1.287) | (1.400) | (1.304) |
| $80^{th}$-$95^{th}$ | 6.008 | 6.099 | 6.623 | 3.569 | 4.141 | 3.882 |
| | (1.145) | (1.178) | (1.143) | (0.826) | (0.879) | (0.808) |
| > $95^{th}$ | 2.085 | 2.592 | 2.594 | 0.412 | 0.168 | 0.670 |
| | (1.459) | (1.746) | (1.486) | (1.006) | (0.951) | (1.010) |
| Tax Burden | | | -4.969 | | | -3.460 |
| | | | (1.208) | | | (1.083) |
| R2 | 0.127 | 0.127 | 0.132 | 0.090 | 0.094 | 0.093 |
| Weighted by Fund Net Assets<br>Lagged Return<br>Percentiles: | Pretax | After-tax | Pretax | Pretax | After-tax | Pretax |
| < 20 | 1.306 | 1.455 | 2.478 | 0.576 | 0.623 | 1.425 |
| | (0.156) | (0.165) | (0.169) | (0.113) | (0.128) | (0.145) |
| $20^{th}$-$40^{th}$ | 0.749 | 1.649 | 1.226 | 0.079 | 0.371 | 0.779 |
| | (0.484) | (0.431) | (0.443) | (0.616) | (0.632) | (0.595) |
| $40^{th}$-$60^{th}$ | 2.984 | 2.402 | 4.030 | 4.688 | 4.068 | 4.979 |
| | (0.798) | (0.915) | (0.799) | (1.132) | (1.055) | (0.853) |
| $60^{th}$-$80^{th}$ | 3.336 | 4.594 | 3.982 | 0.625 | 2.043 | 1.782 |
| | (0.859) | (0.975) | (0.806) | (0.844) | (0.903) | (0.746) |
| $80^{th}$-$95^{th}$ | 3.549 | 4.273 | 4.646 | 3.126 | 3.294 | 3.856 |
| | (0.645) | (0.707) | (0.610) | (0.573) | (0.654) | (0.576) |
| > $95^{th}$ | 1.597 | 1.566 | 2.540 | 0.462 | 0.397 | 1.197 |
| | (1.055) | (1.152) | (1.023) | (1.057) | (1.093) | (1.041) |
| Tax Burden | | | -8.724 | | | -8.045 |
| | | | (0.779) | | | (0.907) |
| R2 | 0.196 | 0.220 | 0.239 | 0.147 | 0.164 | 0.188 |

Notes: Estimates based on relative return measures use 5866 fund-year observations; estimates based on risk-adjusted return measures use 4389 fund-year observations. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 10. Regressions with Additional Controls - Unweighted Linear Models

| Variable | Mean | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| Pretax Return t-1 | | 1.989 | 2.579 | 2.597 | 1.985 |
| | | (0.171) | (0.232) | (0.236) | (0.233) |
| Tax Burden t-1 | | | -4.935 | -4.254 | -1.773 |
| | | | (1.024) | (1.080) | (1.066) |
| Unrealized Capital Gain | | | | -0.213 | -0.087 |
| /Asset Value | | | | (0.100) | (0.058) |
| Lagged Inflow | 32.646 | | | | 0.179 |
| | | | | | (0.023) |
| 8 < Age <= 16 | 0.267 | -17.603 | -16.553 | -15.777 | -9.211 |
| | | (2.023) | (1.985) | (2.001) | (1.849) |
| 16 < Age | 0.227 | -17.529 | -15.297 | -14.658 | -7.659 |
| | | (1.850) | (1.821) | (1.939) | (1.783) |
| Large Blend | 0.257 | 2.381 | 1.645 | 1.865 | 0.844 |
| | | (3.050) | (3.011) | (3.003) | (2.871) |
| Large Growth | 0.103 | 3.347 | 2.336 | 3.278 | 1.495 |
| | | (5.043) | (5.050) | (5.073) | (4.903) |
| Mid-Cap Value | 0.086 | -0.218 | -0.506 | -0.505 | 0.394 |
| | | (3.521) | (3.477) | (3.459) | (3.161) |
| Mid-Cap Blend | 0.089 | 8.258 | 7.142 | 7.663 | 5.378 |
| | | (4.216) | (4.171) | (4.184) | (3.957) |
| Mid-Cap Growth | 0.102 | 11.753 | 9.824 | 11.200 | 8.256 |
| | | (4.999) | (4.911) | (4.952) | (4.714) |
| Small Value | 0.076 | 10.728 | 10.468 | 10.602 | 9.789 |
| | | (4.113) | (4.042) | (4.029) | (3.660) |
| Small Blend | 0.042 | 15.414 | 13.979 | 14.696 | 9.450 |
| | | (5.413) | (5.412) | (5.350) | (4.716) |
| Small Growth | 0.052 | 18.146 | 15.997 | 17.255 | 13.961 |
| | | (5.506) | (5.373) | (5.380) | (5.260) |
| Log Fund Size t-1 | 5.065 | -6.012 | -6.276 | -6.198 | -6.307 |
| | | (0.729) | (0.729) | (0.724) | (0.674) |
| Expense Ratio t-1 | 1.364 | -0.667 | -1.422 | -2.292 | -3.304 |
| | | (2.293) | (2.324) | (2.351) | (2.106) |
| Turnover | 0.839 | -1.310 | 0.048 | -1.109 | -1.412 |
| Ratio t-1 | | (1.005) | (1.225) | (1.263) | (1.313) |
| Load Dummy | 0.595 | 7.680 | 8.367 | 8.766 | 6.937 |
| | | (2.071) | (2.032) | (2.043) | (1.772) |
| Median Market Cap | 11.899 | -0.130 | -0.161 | -0.174 | -0.119 |
| | | (0.105) | (0.104) | (0.103) | (0.098) |
| Price/Book Ratio | 4.951 | 1.414 | 1.499 | 1.764 | 2.072 |
| | | (0.959) | (0.956) | (0.955) | (0.913) |
| Morningstar Rating | 3.103 | 17.432 | 17.262 | 17.076 | 14.126 |
| | | (1.353) | (1.352) | (1.358) | (1.320) |
| R2 | | 0.237 | 0.242 | 0.244 | 0.293 |
| N | | 4591 | 4591 | 4591 | 4591 |

Note. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 11. Regressions with Additional Controls -- Linear Models, Weighted by Fund Net Assets

| Variable | Mean | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| Pretax Return t-1 | | 1.565 | 2.405 | 2.495 | 1.899 |
| | | (0.105) | (0.176) | (0.169) | (0.159) |
| Tax Burden t-1 | | | -7.435 | -6.193 | -3.792 |
| | | | (0.893) | (0.855) | (0.792) |
| Unrealized Capital Gain /Asset Value | | | | -0.450 | -0.241 |
| | | | | (0.072) | (0.064) |
| Lagged Inflow | 21.695 | | | | 0.153 |
| | | | | | (0.022) |
| 8 < Age <= 16 | 0.293 | -13.748 | -12.131 | -10.382 | -6.319 |
| | | (2.461) | (2.303) | (2.294) | (1.983) |
| 16 < Age | 0.534 | -16.539 | -13.566 | -10.413 | -6.510 |
| | | (2.618) | (2.422) | (2.381) | (2.027) |
| Large Blend | 0.303 | -1.026 | -3.016 | -2.231 | -2.635 |
| | | (2.087) | (2.025) | (1.749) | (1.642) |
| Large Growth | 0.137 | -0.313 | -1.512 | -0.512 | -1.438 |
| | | (3.209) | (2.996) | (2.917) | (2.590) |
| Mid-Cap Value | 0.048 | -1.295 | -0.919 | -1.178 | -1.402 |
| | | (2.277) | (2.391) | (2.334) | (2.100) |
| Mid-Cap Blend | 0.061 | 4.900 | 2.013 | 3.698 | 1.533 |
| | | (2.761) | (2.637) | (2.586) | (2.222) |
| Mid-Cap Growth | 0.075 | 10.725 | 6.446 | 8.571 | 5.341 |
| | | (3.320) | (3.300) | (3.184) | (2.997) |
| Small Value | 0.021 | 3.974 | 3.714 | 3.768 | 3.869 |
| | | (2.802) | (2.765) | (2.638) | (2.849) |
| Small Blend | 0.014 | 10.836 | 7.429 | 8.829 | 4.994 |
| | | (6.170) | (6.015) | (5.660) | (5.127) |
| Small Growth | 0.018 | 8.723 | 5.089 | 7.525 | 3.772 |
| | | (4.249) | (4.126) | (3.925) | (3.340) |
| Log Fund Size t-1 | 8.156 | -2.936 | -3.684 | -3.503 | -3.254 |
| | | (0.681) | (0.683) | (0.645) | (0.553) |
| Expense Ratio t-1 | 0.961 | -0.282 | -2.161 | -1.453 | -2.892 |
| | | (2.142) | (2.011) | (1.854) | (1.608) |
| Turnover Ratio t-1 | 0.690 | -2.318 | 1.100 | -1.735 | -1.863 |
| | | (1.387) | (1.354) | (1.405) | (1.224) |
| Load Dummy | 0.572 | 1.376 | 2.055 | 1.998 | 2.284 |
| | | (1.676) | (1.524) | (1.440) | (1.216) |
| Median Market Cap | 17.29 | -0.075 | -0.057 | -0.065 | -0.053 |
| | | (0.061) | (0.066) | (0.065) | (0.053) |
| Price/Book Ratio | 5.178 | 1.575 | 1.446 | 1.850 | 2.001 |
| | | (0.883) | (0.877) | (0.826) | (0.756) |
| Morningstar Rating | 3.738 | 10.764 | 9.916 | 9.219 | 8.137 |
| | | (0.956) | (0.908) | (0.872) | (0.877) |
| R2 | | 0.339 | 0.363 | 0.376 | 0.430 |
| N | | 4591 | 4591 | 4591 | 4591 |

Note. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 12. Net Inflow Regressions Using Different Tax Burden Measures Weighted by Fund Net Assets

| Independent Variable | Tax Measure Aggregates Short Term and Long Term Gains | Tax Measure Splits Short Term and Long Term Gains |
|---|---|---|
| Relative Return t-1 | 2.367 | 2.292 |
| | (0.176) | (0.177) |
| Tax Burden t-1 | -4.460 | -3.686 |
| | (0.790) | (0.790) |
| Unrealized Gains t-1 | -0.212 | -0.228 |
| | (0.073) | (0.073) |
| Inflow t-1 | 0.183 | 0.185 |
| | (0.027) | (0.028) |
| Load Dummy | -0.567 | -0.661 |
| | (1.218) | (1.212) |
| 8< Age <= 16 | -6.234 | -6.295 |
| | (2.116) | (2.109) |
| 16 < Age | -7.109 | -7.281 |
| | (2.218) | (2.224) |
| Log Fund Size t-1 | -1.786 | -1.731 |
| | (0.415) | (0.411) |
| Expense Ratio t-1 | -2.538 | -2.384 |
| | (1.740) | (1.727) |
| Turnover Ratio t-1 | -1.708 | -1.500 |
| | (1.480) | (1.531) |
| R2 | 0.391 | 0.390 |
| N | 3400 | 3400 |

Note. All regressions include year and fund objective dummy variables. Standard errors, in parentheses, are corrected for clustering.

Table 13. Net Inflow Regressions Using Different Tax Burden Measures
Weighted by Fund Net Assets

| Independent Variable | Tax Measure Assumes 10% Tax Rate on Undistributed Gains | Tax Measure Assumes 0% Tax Rate on Undistributed Gains |
|---|---|---|
| Relative Return t-1 | 1.899 | 1.869 |
| | (0.159) | (0.115) |
| Tax Burden t-1 | -3.792 | -2.276 |
| | (0.792) | (0.479) |
| Unrealized Gains t-1 | -0.241 | -0.237 |
| | (0.064) | (0.064) |
| Inflow t-1 | 0.153 | 0.153 |
| | (0.022) | (0.022) |
| Load Dummy | 2.284 | 2.250 |
| | (1.216) | (1.213) |
| 8< Age <= 16 | -6.319 | -6.330 |
| | (1.983) | (1.978) |
| 16 < Age | -6.510 | -6.514 |
| | (2.027) | (2.022) |
| Log Fund Size t-1 | -3.254 | -3.251 |
| | (0.553) | (0.553) |
| Expense Ratio t-1 | -2.892 | -2.766 |
| | (1.608) | (1.605) |
| Turnover Ratio t-1 | -1.863 | -1.780 |
| | (1.224) | (1.247) |
| R2 | 0.430 | 0.430 |
| N | 4591 | 4591 |

Note. All regressions include year and fund objective dummy variables. Standard errors, in parentheses, are corrected for clustering.

Table 14. Regressions with Additional Controls, Institutional Funds
Linear Regressions, Weighted by Fund Net Assets

| Variable | Mean | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| Pretax Return t-1 | | 2.069 | 3.024 | 3.005 | 2.742 |
| | | (0.454) | (0.493) | (0.492) | (0.488) |
| Tax Burden t-1 | | | -7.896 | -7.219 | -5.967 |
| | | | (1.737) | (1.706) | (1.655) |
| Unrealized Capital Gain | | | | -0.185 | -0.057 |
| /Asset Value | | | | (0.129) | (0.121) |
| Lagged Inflow | 25.705 | | | | 0.079 |
| | | | | | (0.022) |
| 8 < Age <= 16 | 0.305 | -4.373 | -3.069 | -2.599 | -1.569 |
| | | (4.295) | (3.875) | (3.821) | (3.632) |
| 16 < Age | 0.046 | -11.043 | -8.272 | -6.713 | -5.000 |
| | | (4.571) | (3.252) | (3.063) | (3.157) |
| Large Blend | 0.466 | 7.620 | 3.118 | 3.460 | 3.763 |
| | | (6.595) | (5.863) | (5.809) | (5.575) |
| Large Growth | 0.069 | 21.580 | 15.838 | 17.008 | 16.610 |
| | | (9.265) | (8.767) | (8.584) | (8.189) |
| Mid-Cap Value | 0.077 | -5.792 | -5.831 | -5.625 | -5.229 |
| | | (5.599) | (5.208) | (5.159) | (5.477) |
| Mid-Cap Blend | 0.029 | 18.651 | 12.266 | 13.816 | 13.643 |
| | | (8.423) | (7.332) | (7.126) | (6.625) |
| Mid-Cap Growth | 0.043 | 9.161 | 5.141 | 6.626 | 5.956 |
| | | (11.062) | (10.577) | (10.223) | (10.035) |
| Small Value | 0.065 | 6.599 | 4.072 | 4.428 | 5.677 |
| | | (6.439) | (5.613) | (5.626) | (5.656) |
| Small | 0.031 | 7.892 | 4.215 | 5.122 | 4.721 |
| Blend | | (7.598) | (7.412) | (7.299) | (7.244) |
| Small Growth | 0.030 | 24.598 | 19.796 | 21.693 | 21.652 |
| | | (11.072) | (9.342) | (9.154) | (8.979) |
| Log Fund Size t-1 | 6.855 | -3.527 | -4.381 | -4.243 | -4.406 |
| | | (1.224) | (1.126) | (1.118) | (1.080) |
| Expense Ratio t-1 | 0.650 | -8.437 | -8.656 | -8.352 | -10.112 |
| | | (6.571) | (5.977) | (5.841) | (5.482) |
| Turnover | 0.505 | -4.593 | 0.574 | -1.172 | -0.396 |
| Ratio t-1 | | (3.518) | (3.193) | (3.644) | (3.481) |
| Load Dummy | 0.000 | -2.228 | -16.233 | -18.447 | -12.678 |
| | | (15.643) | (17.053) | (17.758) | (15.596) |
| Median Market Cap | 22.131 | 0.072 | 0.039 | 0.026 | 0.044 |
| | | (0.216) | (0.202) | (0.203) | (0.200) |
| Price/Book Ratio | 5.348 | -4.015 | -3.445 | -3.166 | -3.078 |
| | | (2.605) | (2.470) | (2.531) | (2.527) |
| Morningstar Rating | 3.742 | 1.770 | 1.142 | 1.151 | 1.167 |
| | | (2.430) | (2.297) | (2.278) | (2.217) |
| R2 | | 0.158 | 0.187 | 0.189 | 0.430 |
| N | | 751 | 751 | 751 | 751 |

Note. Estimates based on sample of institutional funds. All regressions include year dummies. Standard errors, shown in parentheses, are corrected for clustering.

Table 15. Summary Measures of Gross Fund Flows, 200 Largest Funds at Previous Year-end

| | | Net Flow | | Gross Inflow | | Gross Redemptions | |
|---|---|---|---|---|---|---|---|
| Year | N | Unweighted | Weighted | Unweighted | Weighted | Unweighted | Weighted |
| 1994 | 137 | 3.3 | 5.9 | 31.6 | 31.1 | 28.4 | 25.2 |
| 1995 | 159 | 9.4 | 14.0 | 38.6 | 39.5 | 29.2 | 25.5 |
| 1996 | 156 | 4.2 | 8.9 | 34.7 | 35.8 | 30.6 | 26.9 |
| 1997 | 167 | 5.4 | 7.2 | 37.1 | 34.2 | 31.7 | 27.0 |
| 1998 | 67 | 11.1 | 13.4 | 45.3 | 40.3 | 34.2 | 26.8 |
| 1994-98 | 686 | 6.2 | 9.6 | 36.6 | 36.1 | 30.5 | 26.5 |

Note. Sample includes 686 fund-years of data on large domestic equity funds over the period 1994-1998.

Table 16. After-Tax Returns and Gross Inflows and Outflows, 200 Largest Funds at Previous Year-end

Panel A: Unweighted Results

| Explanatory Variable: | Net Inflow | Gross Inflow | Gross Outflow |
|---|---|---|---|
| Excluding Capital Gain Overhang | | | |
| Constant | 41.974 | 74.724 | 32.749 |
| | (6.383) | (9.137) | (4.921) |
| Pretax Return | 2.285 | 2.103 | -0.182 |
| | (0.263) | (0.346) | (0.200) |
| Tax Burden | -5.784 | -5.756 | 0.028 |
| | (1.296) | (2.033) | (1.346) |
| R2 | 0.215 | 0.117 | 0.012 |
| | | | |
| Including Capital Gain Overhang | | | |
| Constant | 50.211 | 89.358 | 39.147 |
| | (7.621) | (10.660) | (5.488) |
| Pretax Return | 2.318 | 2.162 | -0.156 |
| | (0.266) | (0.346) | (0.198) |
| Tax Burden | -5.260 | -4.825 | 0.435 |
| | (1.260) | (2.024) | (1.389) |
| Unrealized Capital Gains As Share of Fund Value | -0.302 | -0.537 | -0.235 |
| | (0.093) | (0.166) | (0.109) |
| R2 | 0.231 | 0.147 | 0.028 |

Panel B: Results Weighting by Fund Assets

| Explanatory Variable: | Net Inflow | Gross Inflow | Gross Outflow |
|---|---|---|---|
| Without Capital Gain Overhang | | | |
| Constant | 9.766 | 32.613 | 22.847 |
| | (1.772) | (2.916) | (2.039) |
| Pretax Return | 2.142 | 1.958 | -0.183 |
| | (0.260) | (0.275) | (0.181) |
| Tax Burden | -5.816 | -7.565 | -1.749 |
| | (1.578) | (2.311) | (1.622) |
| Adjusted R2 | 0.242 | 0.123 | 0.028 |
| Including Capital Gain Overhang | | | |
| Constant | 15.522 | 45.208 | 29.686 |
| | (2.389) | (3.435) | (2.477) |
| Pretax Return | 2.232 | 2.156 | -0.076 |
| | (0.258) | (0.270) | (0.183) |
| Tax Burden | -5.362 | -6.571 | -1.209 |
| | (1.509) | (2.239) | (1.651) |
| Unrealized Capital Gains As Share of Fund Value | -0.361 | -0.791 | -0.429 |
| | (0.097) | (0.167) | (0.111) |
| Adjusted R2 | 0.267 | 0.197 | 0.085 |

Note. Sample includes 686 fund-years of data on large domestic equity funds over the period 1994-1998. Returns are measured relative to S&P500 return.