Money Demand Model of Household Checking Account Behavior:

Are "Bounced Check Loans" Really Loans?

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Abstract:

This paper addresses the controversial bank policy widely employed, yet rarely discussed, of paying – rather than bouncing – bad checks. Individual decisions to maintain checking account balances are modeled. Using the model and checking account customer data, the likelihood of bouncing a check is estimated. These estimations cast doubt on Baumol-Tobin style models applied to checking account allocation decisions. This leaves the literature is without a replacement. Policymakers are currently deciding whether to regulate such programs as a loan or as an account feature. Results show that 35% of overdrafts are intentional which suggests that loan style regulation could be unwise.

1. INTRODUCTION

And you thought credit card interest rates were high. Most banks are somewhat forgiving of good customers who write checks in excess of their checking account balance, (i.e. customers who *overdraft*). By forgiving, I mean that they do not bounce the check but instead opt to pay it, while charging the customer a non-sufficient funds (NSF) fee. Some banks now pay overdrafts for more than just their best customers. For example, consider an NSF fee of $21 due to a check which overdraws an account by $100 and the account remains in deficit for five days. This fee represents a 1500% annual interest rate. If the account is replenished after just two days then the interest rate climbs to 3780%.

Overdrafting is partly a function of maintained checking account balances. But very little work has been done to attempt to understand how consumers allocate resources to checking accounts. This paper is an application of a Baumol-Tobin (Baumol (1952) and Tobin (1956)) style model with extension for precautionary balances (eg. Tsaing (1969)). The paper finds that these models do not work in explaining currently observed checking account allocation decisions. This paper also offers reduced form estimation to answer to a timely public policy question.

The contribution of this paper is thus two-fold. First, given the recent research in understanding the allocation of resources between long term savings and short term debt repayment [see Bertaut and Haliassos (2002) and Laibson, Repetto and Tobacman (2004)] this paper structurally empirically explores how people allocate resources among their short term assets. The paper begins a dialogue on that issue. I model the portfolio problem of allocating between savings account and checking account balances. A data set of individual accounts is used to empirically examine these decisions. A reduced form regression is also estimated and the reduced form fits the data much better than the structural model. This provides evidence that this class of models are not suited for this purpose but the reduce from regressions do show some support for the general structure of the model.

Second, the paper sheds some light on current public policy issues. Bounce protection is attracting attention from regulators and activists. Activists want bounce protection[1] regulated like a loan, while and banks insist that bounce protection programs should be treated like a feature of a savings accounts. This paper addresses whether bounce protection acts as a substitute for payday loans (intentional overdrafts) or for overdraft protection and bounced checks (inadvertant overdrafts). If customers intentionally overdraft as a means of borrowing, then this suggests regulation of bounce protection much like how a payday loan is currently regulated. If account holders overdraft by mistake, then bounce protection is a useful customer service on a checking account and should be treated as such. The paper finds that 35% of overdrafts are unexplained by a model of precautionary savings and thus are considered intentional.

In section (3) a model of accountholder behavior adds structure to this observation. The model is based on the Baumol-Tobin model of cash holding. The data set of checking account transaction records is described in section (4). The model and implies a structural form for nonlinear estimation. Estimation procedure and results for this model and a reduced from model are presented in section (5). The probability that the checking account holder will

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[1]Activists prefer the name “bounced check loans”. Regulators, however, use the term “bounce protection”.

unintentionally overdraft is estimated. In section (6), a comparison of this estimated probability and the actual incidence of overdrafts shows that 35% of overdrafts are intentional, like payday loans. Before turning to the substance, the following section defines bounce protection and shows where this research fits into the literature.

2. Overdrafts and Demand for Money

2.1 What are Overdrafts and Bounce Protection?

The vast majority of checks draw on sufficient funds and clear without any problem. But when an *overdraft* is presented for payment several things can happen. The depository institution (commercial bank, credit union, or savings & loan) can transfer money from a savings account to cover the overdraft. They can loan money to the customer to cover the check at a predetermined interest rate. They can pay the check allowing the account to have a negative balance (with no interest charged). Or they can return, or *bounce*, the check.

The first two options are called *overdraft protection*. Usually, the customer applies for overdraft protection. When a savings account is used for overdraft protection, the depository will transfer money from a designated savings account to cover the overdraft and charge a small fee, usually between $2 and $5. With a line of credit based overdraft protection, the depository loans enough money to cover the overdraft, usually with an interest rate comparable to credit cards and usually without a fee. In June 2003, 90% of banks and 78% of credit unions offered one or both kinds of overdraft protection.

For customers not enrolled in overdraft protection or for those whose savings account or line of credit is exhausted, the depository faces a decision – bounce the check or pay it. The depository can always bounce the check, but for *good* customers – high net worth or first time overdrafters – often a depository officer decides to pay the check, allowing the account to have a negative balance. In recent years, several depositories have started paying overdrafts for more than just their best customers. Many use more systematic methods for determining which overdrafts to pay and which to bounce. A policy of paying overdrafts is called a *bounce protection* program. The definition of bounce protection is summarized in figure (1).

Figure 1
Definition of Bounce Protection

An overdraft check is presented for payment. What can happen?

If customer has Overdraft Protection:

Î Depository transfers money from another account at the depository

Ï Depository loans money to cover the overdraft

If no overdraft protection, bank can:

Ð Bounce Protection:
Pay Overdraft checks

Ñ Bounce Overdraft checks

2.2 Overdrafts and Demand for Money in the Literature

With overdraft protection such a new phenomenon and the regulatory and media scrutiny of the practice less than two years old, it should not be surprising that no published work looks into the practice of routinely paying overdrafts. It is more surprising, though, that the Fed's research staff is not studying this issue and that no literature has specifically addressed the tradeoff between savings and checking account balances or the likelihood of bouncing a check. The contribution of this chapter is in providing a theoretical structure to think about overdrafts, estimating this model and using it to address the critical economic questions that should affect regulation of the practice.

Bar-Ilan (1990) broadened a deep money demand literature by allowing for negative balances. Customers pay interest on such balances. Thus he modeled "overdraft protection line of credit." He, as I, has extended a money demand literature that started with the Baumol (1952) and Tobin (1956) model of transaction demand for money.

We are interested in the demand for money theory because underlying the consumers' problem is a money demand function. Accountholders maintain a balance in order to facilitate transactions but because account behavior is somewhat stochastic they must hold a buffer of money in order to prevent overdrafts. Thus, the transactions and precautionary demand for money are important.

Baumol and Tobin describe a simple framework for the transactions demand for money. They analyze the tradeoff between holding cash and a bond; or, more generally, between a non-interest-bearing asset which can serve as a medium of exchange (such as checking accounts) and an interest-bearing asset unsuited for payments (such as savings accounts). They derive the optimal pattern of cash holding as a function of the interest rate and cost of transferring wealth between the two assets.

Miller and Orr (1966) followed allowing stochastic receipts and expenditures. Milbourne (1983) relaxed further assumptions. I maintain the characteristic of the Baumol-Tobin model that receipts begin a period and expenditures happen throughout the period. This framework better represents household financial patterns, where the Miller and Orr setup might be better for modeling business finances.

Whalen (1966), Tsiang (1969) and Frenkel and Jovanovic (1980) tried to capture the precautionary demand for cash by adding a stochastic element to expenditures. Tsiang, in particular, allows expenditures to vary with a generic density function. Thus, actors hold some cash for transactions as in the Baumol-Tobin model but they also hold precautionary cash balances. The level of these balances is dependent on the interest rate, the cost of transfers, and the likelihood and cost of unexpected swings in cash balances. I adjust Tsiang's model to fit the specifics of the banking industry.

Bar-Ilan (1990) built on Frenkel and Jovanovic's model adding the possibility for both positive and negative balances in the transaction account, with the consumer paying or receiving interest on the balance. He modeled an overdraft protection line of credit, removing zero as a boundary point of account balances. The current analysis is concerned with bounce protection, which happens when an overdrafter does not have an overdraft protection loan available. In my model, zero balance is a significant point. A further development of the model would include a first stage where consumers choose to have this type of overdraft protection and a second stage where consumers write checks, potentially in excess of their positive transactions account balance.

Boeschoten (1998) estimated a reduced form model of transactions (cash, in his case) balances which was based on the Baumol-Tobin model. He found a relationship between transactions balances and cash withdrawals per month. His primary interest is selection of payment method, but he also finds that cash balances respond to the cost of maintaining such balances.

The following section adapts the Baumol-Tobin-Tsiang model to explain overdrafts. I model customers' choices to allocate money to checking and savings.

3. Demand for Account Balances – Checking v. Savings

Checking account customers who perceive a high cost of overdrafting will behave so as to avoid such an occurrence; those who see a lower cost of overdrafting will not take costly measures to avoid overdrafts. One way of avoiding overdrafts is to maintain a cushion in the checking account so that checks are less likely to bounce. Thus, we expect those with a high perceived cost of overdrafts to maintain a high cushion in their checking account. This analysis is formalized using a model of money demand.

Baumol (1952) and Tobin (1956) created a model where customers choose between bonds and cash. Cash can be used as a medium of exchange; bonds can not but earn more interest.[2] Using the textbook definition of money (M2 or greater), both savings and checking accounts would be money, and a bond would be an investment instrument.

The context of this paper, however, is overdrafting by an accountholder without overdraft protection to sweep money from savings accounts. So while customers have immediate access to their checking accounts by writing checks, they have no such access to their savings accounts. If they write checks which overdraw their checking accounts, they will bounce regardless of the

[2] In their model, cash earns no interest but the interpretation of the model could be generalized to one where money earns interest (e.g. NOW accounts) but bonds pay a higher interest rate. Then the model's interest rate would be thought of as the interest differential between money and bonds.

savings account balances. In order to access savings account money, they need to act, transferring money from savings to checking.

In this paper, checking accounts serve as money – an asset which can be used in its current form to facilitate transactions. Saving accounts fit the definition of a non-transaction asset – one which must be transferred in order to facilitate transactions but earns a higher rate of interest than money. I now model the allocation choice of checking versus savings.

3.1 Checking v. Saving

Suppose that the accountholder expends *T* dollars in a steady stream through the pay period. He receives an income, *I $ T,* which is sufficient to afford more than the necessities of life. He may save most of this excess or he may spend it on luxury goods but he has excess income which could go to a savings account, a checking account, or purchases.

Transfers between savings and checking cost $a + bx$ when x dollars are transferred. If the interest bearing assets were in a broker traded account, such as Tobin's "bonds", then proportional costs would be relevant. Transfers between checking and savings accounts within a single depository have no explicit cost. Implicit costs – primarily the time to make the transaction – do not increase with the transfer amount. Indeed, the accountholder might be more annoyed if a $5 transaction were occupying his time than if he were transferring $500. Therefore, the parameter value in the present situation is $b=0$, and the transfer cost is a.

Variable Definitions

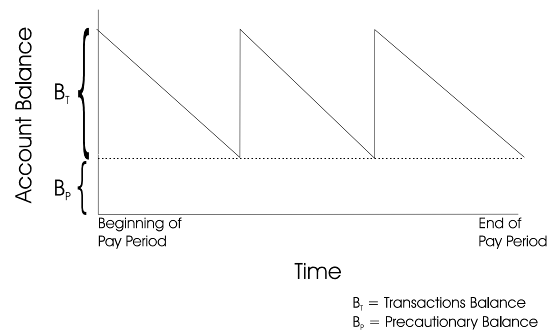
T = transactions amount per pay period
I = income
b = proportional transfer cost
a = flat cost for planned transfers
α = non-monetary cost of overdrafting
NSF = Non Sufficient Funds fee is charged by DIs for overdrafts
n = number of transfers from savings to checking per pay period
B_T = transactions balance
B_P = precautionary balance
$B = B_T + B_P$ = total checking balance
r = excess interest rate of savings over check
E(L) = expected loss from an overdraft being presented for payment
p(x) = probability of checks of totaling x being presented for payment
P(B) = probability of an overdraft being presented for payment

Savings accounts pay an interest rate, *r* (in excess of that paid on checking accounts). An accountholder can earn interest on money received and spent in the same pay period by transferring a part of his paycheck to a savings account upon receipt and earn interest until that money is needed for purchases. The accountholder wants to maximize savings balances to earn interest at the lowest cost of transfers between savings and checking accounts. He leaves a portion of his paycheck in checking and pays expenses until the account balance drops to zero. Then the accountholder transfers money to checking and spends until it is depleted. This pattern continues until the new paycheck when the cycle starts again. This behavior gives the sawtooth pattern of checking account balances depicted in figure (1).

The accountholder's problem, then, is to choose the amount of money, B_T, to be transferred into the checking account during each checking account replenishment cycle and the number of cycles, *n*.

Solve for B_T in terms of *n* Baumol, Tobin and Tsiang allow for the possibility that the transactions balance held immediately after a paycheck is received could be larger than that held after each subsequent checking account replenishment. Graphically, this would mean that the first tooth is larger than the others.

Figure 2
Checking Account Balances



When there are no proportional costs of transferring money between checking and savings (*b=0*), the difference between the first peak and subsequent ones disappears. The intuition for this is simple. The reason to hold more money during the first replenishment period is because any balances held the first period are never transferred to savings, unlike those used in later replenishment periods. The accountholder can avoid paying proportional transfer costs on balances held in checking during the first cash replenishment period, making him favor the first replenishment period. However, when the proportionate cost of transferring money is zero, it does not matter how much is transferred each time, only how many transfers are made, so no distortion exists.

Once we know that the peak balances of the checking account replenishments are equal, the connection between B_T and n is straightforward. Given total expenditures in the pay period, T, once the accountholder decides how many times to replenish the account, n, he then transfers an equal amount, B_T, each time. So given n, B_T is:

$$B_T = \frac{T}{n} \tag{1}$$

But consider, as Tsiang did, that disbursements are less predictable than the Baumol-Tobin model assumes. Then a need emerges for precautionary money demand. In this case, an accountholder is uncertain about the exact date when a check will clear, and T is an estimate of purchases in a given time period.

Accountholders often fail to record checks written or fail to balance their checkbooks between pay periods. Some withdrawals are automatic, taken without the action of the accountholder.

All these factors add uncertainty as to the path of disbursements and the exact path of disbursements is not as steady as the graph implies. This uncertainty raises the possibility that a check could clear sooner than expected; thus becoming an overdraft or that the accountholder would write checks in excess of T.

In any pay period, the possibility exists of an overdraft being presented for payment. If customers draw their account balances down to zero before transferring more money from savings, then they are almost certain to bounce checks 50% of the time. If they plan to replenish the money before the account balance reaches zero, then they hold money in a transaction account at an interest loss which they, on average, do not spend. They hold these balances as a precaution against bouncing a check. These balances are called Precautionary Balances (B_P). Balances then are the sum of precautionary and transactions balances ($B=B_T+B_P$). The path shown in figure (1) is the expected path; the true path is not smooth for the reasons listed above and the consumer's problem is to balance this interest loss against the possible cost of an overdraft.

The strategy for solving for the optimal values of B_T and B_P derives from Tobin and Tsiang. I solve for B_P in terms of n and for n in terms of B_P – which implies a value for B_T through equation (1) . First consider B_P.

Solve for B_P in terms of n The benefit of holding precautionary checking balances is the reduction in expected loss (*E(L)*) from an overdraft being presented for payment. The cost of holding precautionary balances is the foregone interest income which could be earned if the balances were in savings. The cost is simply r, the excess of interest over that earned on a checking account.

The expected loss, given a level of precautionary checking account balance (B_P), is the cost of an overdraft being presented for payment multiplied by the probability of such an occurrence. The explicit cost of an overdraft being presented is the NSF fee which the depository charges (*NSF*) plus the implicit costs of such an occurrence (α): $\alpha + NSF$. If the check is bounced, then the implicit cost (α_{NSF}) is the inconvenience of dealing with the problem, the embarrassment, the cost imposed by the merchant to whom the check was written, and other consequences of the bounced check. If the institution pays overdraft checks, then the implicit cost (α_{OD}) is simply the inconvenience of dealing with the problem. Let $\Delta^{\alpha}{}_{OD}$ be the difference between the two implicit costs ($\alpha_{OD} - \alpha_{NSF}$), which is expected to be negative because the costs seem to be less when depositories pay overdrafts. This is also the increment in customer cost from Bounce Protection.

The probability of overdrafting varies with the account balance. Specifically, if $p(x)$ is the probability density function of checks totaling x being presented for payment before the next scheduled balance replenishment, then the cumulative distribution function ($P(x)$) is the probability of checks totaling up to x being presented for payment. This is the probability of not overdrafting given an account balance of x. Or, the probability of checks being presented totaling *more* than the current balance in the account is $1 - P(x)$. This is evaluated at B_P since this is the lowest planned account balance during the pay period. Interpret this as the probability of total checks being presented for payment in excess of planned expenditures plus the cushion, B_P.

The expected loss from holding precautionary balances can then be written as:

$$E(L) = (\alpha + NSF)\left[1 - P\left(B_P\right)\right]$$

This is the expected loss for each checking account replenishment cycle. In order to convert this into the expected loss for each pay period, multiply it by n, the number of replenishment cycles per pay period.

At the optimal holding of precautionary balances, the marginal cost of holding them equals the marginal benefit. The marginal benefit is the reduction in the expected loss and the marginal cost is the foregone interest income which is a constant, r. Setting this equal to the marginal benefit provides:

$$r = -n(\alpha + NSF)\left[-p\left(B_P\right)\right] \tag{2}$$

This equation implicitly defines B_P in terms of n, which is endogenous, and various costs, which are exogenous from the standpoint of the individual. The equation reads that the dollar loss from overdrafting times the probability of overdrafting for the marginal precautionary dollar times the number of times the account comes close to overdraft range must equal the interest lost on the marginal precautionary dollar deposited in a checking account. Now that we have defined B_P in terms of n, we turn to the determination of the optimal number of checking account replenishments during the pay period.

Solve for *n* in terms of B_P If n were a continuous variable, solving for n would simply involve defining the cost function of possibly overdrafting and deriving it with respect to B_P and B_T much like Tsiang does[3]. This method ignores the necessity that n be an integer. If n were large, then solving for a continuous value of it would be a reasonable approximation. If the accountholders receive annual pay, as is the case for some fellowships, then this would be a reasonable approximation. But most wage earners, paid biweekly – the case for much of the data set – are unlikely to transfer money between saving and checking more than once or twice.

I solve for n as Tobin does. Equation (1) says that given n transactions the optimal size and timing of transactions is to equally size and space them through the time period. So at the beginning of the pay period the accountholder puts $B_T = T/n$ into the checking account and the rest of future transactions balances, $T - B_T = T(n-1)/n$, into savings temporarily. The *average* savings account balance[4] over the pay period (or portion of the savings account balance that is actually transactions balances temporarily in savings) is one half of this,

$$\tfrac{1}{2}\frac{n-1}{n}T,$$

which provides a return of

$$\frac{n-1}{2n}Tr.$$

[3] Baumol has a similar procedure but in his simpler case he can write the marginal cost function directly, bypassing the calculus.

[4] For more explanation and graphs which illustrate this point see Baumol (1952).

The marginal return of increasing from n to $n+1$ transfers is

$$\frac{(n+1)-1}{2(n+1)}Tr - \frac{n-1}{2n}Tr$$

which simplifies to

$$\frac{Tr}{2n(n+1)}.$$

And the marginal cost of increasing the number of planned transfers from n to $n+1$ is:

$$a + E(L)\Big|_{B_p(n+1)}$$

where a is the inconvenience cost of making a scheduled transfer between savings and checking. And the second term is the expected loss from overdrafting when B_P is calculated from equation (2) given $n+1$ transfers rather than n. An accountholder would choose to make n transfers during a pay period if

$$(n-1)\left[a + E(L)\Big|_{B_P(n)}\right] < \frac{Tr}{2n} \leq (n+1)\left[a + E(L)\Big|_{B_P(n+1)}\right]$$

This inequality works for *n$2*. There will be only one balance replenishment at the time income is received ($n=1$)[5] if:

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[5] Tobin and Tsiang quibble about whether it is truly $n=1$ or $n=0$. It is convenient, though, to think of this as $n=1$ so that n will equal the number of saw teeth – the number of cash replenishment cycles.

$$\frac{Tr}{4} \le a + E(L)\Big|_{B_P(2)}$$

Using these inequalities and equation (2) and given a functional form for *P(.),* one could solve for the optimal n and B_P. The solution method would most likely be guess and verify: picking an n, calculating B_P from equation (2), checking whether the inequalities are satisfied, and if not, adjusting the guess of n as appropriate, and repeating until the inequalities are verified.

3.2 Checking v. Spending

Many checking accountholders do not have savings accounts. In my data only 123 of 1949 customers have checking accounts. So how would the model change if savings accounts disappear? Less than would initially appear.

Without savings accounts there would be no sweeping between savings and checking ($n=1$). Then equation (1) implies that $B_T = T$. However, the need for precautionary balances does not disappear just because most of the Baumol-Tobin analysis is gone. The benefit of precautionary balances are unchanged but the cost of precautionary balances, opportunity cost of money, changes.

A consumer who does not save is trading precautionary balances for current consumption, either by borrowing or foregoing consumption. If the consumer borrows then the marginal cost of precautionary balances is clearly the credit card interest rate (r^b). Suppose, however, that the consumer does not borrow. Then the relevant cost of precautionary balances is the consumer's discount rate on consumption (r^c), which we know to be less than the credit card rate (otherwise the consumer would borrow to consume).

Thus if the consumer has no savings, equation (2) becomes equation (2'):

$$r^b \leq -n(\alpha + NSF)\left[-p(B_P)\right] \tag{2‘}$$

One issue to be investigated is whether customers overdraft intentionally as a means of getting a quick loan or whether they are overdrafting by mistake. Certainly both occur, but this model can be used to separate the two effects. More in section (6) on this, but the key to notice here is that once *P(.)* is known, it implies a rate of overdrafts caused by the unpredictability of receipts. Any overdrafts beyond this amount is intentional.

The following section describes the data which are used in the estimation. The estimation results are presented in section (5).

4. The Accountholder Data

I employ a data set of transaction records from 1,950 checking accounts to estimate accountholders' demand for cash balances and separate the incidence of intentional from accidental overdrafting. I obtained the data set from a small depository institution in the Midwest. It includes customer information and all transactions with associated balances from May, June, July and August 2003. Any transaction which leaves the account in a negative balance is an overdraft transaction. In addition, I observe the cumulative number of overdrafts

Table 1: **Summary Statistics of Accountholder Data Set**

Variable	Obs	Mean	Std. Dev.	Min	Max	Units
Transactions Balance (B_T)	1950	1152	1106	105	22541	$
Precautionary Balance (B_P)	1950	1433	3874	–1655	91092	$
Income (I)	1950	3175	2908	96	42744	$ per Month
Payperiod Length (n)	1950	13.4	6.603	3	58	Days
Savings Acct Balance	124	3534	5287.0	–10	37456	$
Interest Rate on Savings[a]	123	0.83	0.276	.21	1.25	% Rate
Interest Rate on Checking[a]	1950	0.05	0.092	0	0.34	% Rate
Positive Only[a]	925	0.10	0.112	.002	0.34	% Rate
Overdraft in Sample[b]	1950	.242	–	0	1	Indicator
Sample Overdrafts[c]	471	2.8	2.44	1	14	# of PayPds
Overdraft in the Past[d]	1950	.591	–	0	1	Indicator
Past Overdrafts[e]	1153	43	88.6	1	741	# of ODs
Sample Overdrafts[f]	1153	1.1	2.09	0	14	# of PayPds
No Past Overdrafts						
Sample Overdrafts[g]	797	0.018	0.176	0	3	# of PayPds
Age	1948	45	13.3	18	94	Years
Joint Acct	1950	.517	–	0	1	Indicator

[a]Average Daily Interest Rate
[b]Indicator for whether or not individual overdrafted during sample period
[c]Number of pay periods in which individual overdrafted in sample conditional on overdrafting once in sample
[d]Indicator for whether or not individual overdrafted since account was opened
[e]Number of overdraft checks since account was opened conditional on overdrafting once since opening account
[f]Number of pay periods in which individual overdrafted in sample conditional on overdrafting once since opening account
[g]Number of pay periods in which individual overdrafted in sample conditional on never overdrafting since opening account

since the account was opened, savings account balance and all stop payment requests. This institution, like many others, does not advertise its bounce protection policy, so most accountholders first learn of the policy when they overdraw their account for the first time.

Table (1) shows summary statistics for the data set. The average customer receives biweekly paychecks for an income over $3000 per month. Note here that I observe only income which enters this institution. Any income diverted to accounts at other institutions is not observed. Few have a savings account at the same institution, but those who do maintain an average balance over $5000. The interest rate reported is the average daily interest rate where the daily interest rate fluctuates with the account balance. In particular, a savings account with less than $500 earns no interest and a checking account with under $2000 earns no interest. Approximately half of the accounts are joint accounts and the age distribution looks representative of the population.

One quarter of accountholders overdraft during the sample period for an average of 2.8 pay periods in which they overdrafted. Almost 60% of accountholders have overdrafted at least

Table 2: **Distribution of Overdrafts by Age and Income**

	Percent of Category Population[a]					Number of Individuals in Category					
Number of Lifetime Overdrafts:	0	1-4	5-15	16-100	100+	0	1-4	5-15	16-100	100+	Total
By Age:											
18 – 35	25	21	21	24	10	118	99	101	114	46	478
36 – 44	37	18	21	17	7	191	93	105	86	36	511
45 – 53	46	17	14	16	7	226	81	67	79	34	487
54 and better	55	18	11	12	4	262	83	53	55	21	474
By Income:											
up to $1500	40	17	19	18	7	192	79	88	84	32	475
$1500 – $2500	41	18	17	16	8	209	95	86	85	41	516
$2500 – $4000	45	20	12	18	6	215	92	59	86	29	481
$4000 and up	38	19	19	17	7	181	90	93	79	35	478
Total	41	18	17	17	7	797	356	326	334	137	1950
Overdrafts as % of Checks Written:	0	< .18	< .68	< 4.5	> 4.5	0	< .18	< .68	< 4.5	> 4.5	Total
By Income:											
up to $1500	40	5	9	20	25	189	24	43	95	116	467
$1500 – $2500	40	12	15	19	14	207	60	75	99	73	514
$2500 – $4000	45	16	14	17	9	215	75	66	82	43	481
$4000 and up	38	23	16	16	8	181	108	75	78	36	478
Total	41	14	13	18	14	792	267	259	354	268	1940

[a]Rows Percentages sum to 100%

once since opening their accounts. The average number of overdrafts is 43 in a very skewed distribution. Those who have overdrafted in the past average 1.1 overdraft pay periods in the sample compared to 0.018 overdrafts for those who have never previously overdrafted.

Transactions and precautionary balances are defined in section (3) and are depicted in figure (1). They are observed in the data by searching for the peaks and troughs immediately before and after major deposits (paychecks). Then precautionary balance for each customer are the average level of the troughs for that customer. Transactions balances are the difference between the average peak and average trough for the customer.

Table (2) shows the joint distributions of Overdrafts vs Age and Overdrafts vs Income. Non-overdrafters are skewed toward older customers possibly reflecting a generational stigma toward bounced checks which is weaker among the younger generations. We see this trend even though older accountholders have had their accounts longer. In all categories greater than five overdrafts, younger accountholders dominate.

The second tier of Table (2) shows number of overdrafts by income. There are no patterns in this data indicating that people of all income levels overdraft equally often. However, the bottom tier tells a different story. Looking at overdrafts but controlling for the number of checks written reveals that low income individuals do indeed bounce more checks measured as a percent of total checks written.

The following section reports estimation results.

5. Estimating the Likelihood of Overdrafting

I am interested in the cost of overdrafting and the likelihood of bouncing a check, given account balance. The primary estimation strategy is to use equation (2) as a structural model to estimate *P(.)*, the probability of accidentally overdrafting given a level of precautionary balances, B_P. I use a logistic form for *P(.)* to guarantee that the probability is between zero and one. And estimate the equation using nonlinear least squares. The theory suggests that *P(.)* varies with B_P. However, the function could depend on B_T, n and personal characteristics. The expression to minimize is then

$$\left[\alpha + OD_i\left(\Delta^{\alpha}\right) + NSF_i\right] p\left(B_{P_i} : B_{T_i}, n_i, \chi_i\right) - \frac{r_i}{n_i}$$

where the cost term (in square brackets) has been adjusted by adding $OD_i \bullet (\Delta^{\alpha})$. The variable OD_i is an indicator for those accountholders who know that the depository will pay most overdrafts. Thus, the cost of overdrafting for those expecting a bounced check is $\alpha + NSF$ and for those who expect overdrafts to be paid is $\alpha + \Delta^{\alpha} + NSF$.

In order to estimate values for α, the implicit cost of bouncing a check; Δ^{α}, change in that cost for customers who are aware that their overdraft will most likely not bounce; and β, the vector of coefficients in $P(x\beta)$. I estimate equation (3),

$$\frac{r_i}{n_i} = \left[\alpha + OD_i\left(\Delta^{\alpha}\right) + NSF_i\right] p\left(B_{P_i} : B_{T_i}, n_i, \chi_i\right) + \varepsilon_i \qquad (3)$$

where $\mathbf{g}_i$ is iid and normally distributed. I use nonlinear least squares to estimate this equation and the results are reported in Table (3).

Figure (1) provides the intuition for calculating B_P and B_T from transaction records. The core of the algorithm is to search for the peaks and valleys. The unit of observation is a customer so B_P and B_T are averages over the four months of observation. Since it is difficult to distinguish between paychecks and other transfers, I divide by n so that the left hand side is interest per cash replenishment cycle rather than per pay period. Remember that in this estimation B_P is the dependent variable even though it is not on the left hand side.

The transactions balances also appear in the estimation. Since B_T is determined by income and n, and income is exogenous, and the number of cash replenishment cycles is exogenous, I take B_T to be exogenous also. I can take the number of cash replenishment cycles to be exogenous because the short pay periods of most customers – 2 weeks on average – do not leave much time for multiple sweeps between savings and checking. Indeed, a cursory glance at the data corroborates this assumption.

The variable OD_i indicates customers who are aware of this financial institution's policy of paying overdrafts. I assume that customers who have bounced a check at least once since obtaining their checking account know about the bounce protection policy and the others do not. This assumption appears reasonable since they do not advertise this policy, so only customers who have written an overdraft which was subsequently paid are aware of the policy.

The interest rate is the opportunity cost of the money which is used for precautionary balances. The models presented in table (3) differ in the interest rate used and sample. Each is a nonlinear least squares estimation of equation (3). The model in column (1) defines interest rate as the credit card rate which is charged by this institution. This choice was made because the opportunity cost of holding money, for most people, is the foregone consumption; the credit card

Table 3: **Estimating Probability of Overdrafting – Non-linear Least Squares**

	[a]With Credit Card Rate for All Customers (1)		[b]With Savings Intrest Rate (2)		[c]Customers With Savings Accounts (3)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Intangible Cost						
α	– 10.67**	0.068	– 10.64**	0.239	– 17.59**	3.000
$\Delta\alpha$	0.011	0.028	0.078	0.095	–0.029	0.096
Covariates in P(.)						
Constant	3.52**	0.011	3.66**	0.037	4.82*	2.479
Transaction Balance	1.44[e]	1.84[e]	4.60[e]	5.81[e]	12.6[e]	32.5[e]
Precautionary	–0.86[e]	0.55[e]	–3.22[e] *	1.63[e]	9.09[e]	24.3[e]
Balance	0.043**	0.004	0.054**	0.016	–0.097	0.088
Joint account	–41[e]	159[e]	– 0.0012*	0.0005	–0.0024	0.0024
Age	0.019**	0.006	0.017	0.020	–0.037	0.108
Gender (Male)	–0.010	0.009				
Have Savings	– 0.072**	0.0004	– 0.072**	0.001	–0.073**	0.018
Account						
Checking replenish cycle length						
Estimate of P(.)[d]						
10th percentile	.043		.039		.015	
25th percentile	.045		.041		.016	
Median	.059		.055		.020	
Mean	.070	.000028	.064	.000088	.024	.0110
75th percentile	.074		.068		.026	
90th percentile	.113		.105		.038	
Max	.249		.250		.076	
Number of Obs	1950		1949		123	

Significant at: *95%, **99%

[a]Interest rate is calculated using the credit card rate, a proxy for the discount rate on consumption.

[b]Interest rate, for accountholders with savings accounts, is calculated using the savings account rate.

[c]Sample is restricted to those accountholders with savings accounts.

[d]Calculated from fitted values.

[e]In One Millionths

rate is used as a proxy for the discount rate on forgone consumption.

The model in column (2) recognizes that some accountholders have additional funds in a savings account (known to the researcher). Since the interest rate paid on savings accounts is lower than the credit card interest rate, this would be the opportunity cost of funds stored in checking for those accountholders who have a savings account. Therefore, in model (2), interest rate is defined as the interest rate this institution pays on savings accounts for any account with a savings account and the credit card rate for the rest.

A note should be made about how the savings account rate is calculated from the tiered rate structure of these accounts. For any account which spends the whole sample period in the same tier, the relevant interest rate is obvious. However, for any account which spends part of the sample in one tier, an average daily interest rate is used. For example, suppose the bank pays 1% interest on accounts of below $1000 and 2% on accounts of $1000 or above. If an accountholder spends half of the sample period with $900 in the account and the other half with $1000, then the interest rate for this account would be 1.5%. Similarly checking accounts earn interest if more than $2000 is kept in the account so I calculate the interest rate paid on checking analogously. As noted above, the relevant interest rate on savings in the model is the interest rate spread of savings over checking.

Finally, column (3) of table (3) reports the results of when the sample is restricted to accountholders who have savings accounts. The interest rate used is the savings account rate described above. The problem with model (3) is that the sample is too small to get statistically significant estimates of many variables.

Notice first that in both of the full sample models those who have a higher precautionary balance are less likely to overdraft, though they are a little shy of 90% significant in model (1). Those with longer pay cycles are less likely to overdraft. Joint accountholders are more likely to

Table 4: **Estimating Probability of Overdrafting – Reduced Form Estimation**

	Overdrafts in Sample (4) - Logit		Overdrafts in Sample (5) - OLS		Past Overdrafts (6) - OLS	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Intangible Cost						
α	98.59[a]					
Δα	–82.23[a]					
Covariates of P(.)						
Constant	65.2**	6.61	1.58**	0.095	21.3**	0.986
ln Transaction Balance	0.302**	0.108	0.010	0.006	0.144*	0.063
ln Precautionary Balance	–5.71**	0.567	–0.119**	0.007	–1.28**	0.073
Joint account	–0.132	0.139	–0.012	0.008	–0.320**	0.088
ln Age	–0.860**	0.185	–0.068**	0.012	–1.78**	0.129
Gender (Male)	0.088	0.150	0.014	0.011	–0.043	0.111
ln Checking replenish cycle length[d]	0.489**	0.131	0.049**	0.008	–0.286**	0.088
P(.) Estimate Value[a]						
10th percentile	.0004					
25th percentile	.005					
Median	.022					
Mean	.041					
75th percentile	.051	.0085				
90th percentile	.094					
Max	1.00					
Number of Obs	1784		1950		1950	

Significant at: *95%, **99%

[a]Calculated from fitted values.

overdraft, possibly due to the added friction of communication between the two accountholders. Older accountholders are less likely to overdraft according to model (2) but model (1) fails to capture this effect. Model (1) finds that men are more likely to overdraft than women whereas model (2) fails to capture this effect.

The estimated coefficients for α are negative but not enough to offset the explicit cost of overdrafting so *NSF+α* is positive but less than \$20. This might be believable for paid overdrafts but for bounced checks where the merchant tacks on another \$20 or so it is rather implausible. In addition, those who know their depository will pay overdrafts perceive a higher (though not significant) cost of overdrafting. This counters what I expect. The negative sign on *α* and the positive sign on *Δα* are consistent with those who have never overdrafted underestimating the cost of overdrafting.

Because of this implausibly low customer's cost of overdrafting and other reasons which are highlighted in the next section, I proceed to a more direct method for estimating the probability of overdrafting. This second method, in contrast to the one just presented, uses observed overdrafts to estimate the probability of overdrafting. I consider this a weakness of the second method but the results are much more plausible.

Equation (3) identifies the probability of bouncing a check from the assumption that accountholders set their precautionary balances to be consistent with their savings interest rate. In the second method, I use fewer assumptions by using the observed overdrafts directly. Table (4) shows the results of simple log-linear regressions of the probability of overdrafts regressed on explanatory variables. Model (4) is a logit regression where the dependant variable is the percent of pay periods in which an accountholder overdrafts[6] during the four month sample

[6] Technical note: STATA will allow only a boolean variable as the dependant variable of a logit regression. To circumvent this restriction, I create an observation for each person-pay-period which is zero if no overdraft occurs in the person-pay-period. I then cluster the regression by account so that effectively I have only one observation per account. Therefore, effectively, there are 1784 observations and the dependent variable is the percent of pay periods in which the account was in deficit.

period. I restrict attention to those accountholders who are not chronic overdrafters, those whose history of overdrafts is less than one per month.

For comparison, in model (5), I provide the results of the same estimation using a linear rather than a logit form. The results of this model are similar to those of model (4) except that it fails to capture the significance of transactions balances (expenditures) in explaining the likelihood of overdrafting.

The model (6) dependant variable is the number of overdrafts per year since the account was opened. Note here that the average number of past overdrafts is much higher than sample period overdrafts, 43 compared to 2.8. This scale difference explains the roughly 20-fold difference in the coefficients between models (5) and (6).

In all three models, precautionary balance is a significant variable in the probability of overdrafting. Older account holders are less likely to overdraft. Checking account replenishment cycle is significant at the 99% level in all three models but it is positively correlated with overdrafts in the sample period (fourth and fifth models); whereas it is negatively correlated with overdrafting in the past. This is a puzzle.

The lower portion of tables (3) and (4) show the distribution of the estimated probability of overdrafting. I calculate the fitted values of *P(.)*, the probability of overdrafting, based on each equation. For models (1), (2) and (3), I first calculate the fitted values of the right hand side of equation (3). Then I divide the fitted values by $(a + OD_i \Delta^a + NSF)$. For this, I naturally use the estimated a and Δ^a. This leaves the remaining part of the right hand side of equation (3) which is the estimated probability of overdrafting. The 10th, 25th, 50th, 75th, and 100th, percentiles of these fitted values are reported on the bottom portion of table (3). The mean and standard deviation of these estimates are also reported. For model (4), I report the fitted values of the right hand side, the probability of overdrafting.

The distribution is more disperse with the direct estimation than with the structural equation of models (1), (2) and (3); but the center of gravity is much lower with direct estimation. Notice that the probability of overdrafting ranges from .04% in the 10th percentile to 9.4% in the 90th percentile to 100% in the 100th percentile for the direct estimation model (4). By contrast, model (2) ranges from a 2.9% to a 10.5% to a 25% chance of overdrafting respectively – much less disperse. The mean and median though are higher for the structural model (2) – 6.45 and 5.5% compared to just 4.1% and 2.2% for model (4).

I calculate the perceived cost (α) of an overdraft in model (4) by first calculating each individual's probability of overdrafting (*P(.)*) and then solving for α. in equation (3) for each observation. I report the geometric average across individuals so that a few very large values do not dominate the average. First, notice that the estimates of α and Δ^{α} are reasonable indicating that maybe the equation is fine but the functional form is the problem in the structural estimation. Notice also that those who have never overdrafted in the past perceive the cost of an overdraft to be $100 while those who have overdrafted at least once perceive the cost to be $16. By means of comparison, consider that those who overdrafted only once in the past perceive a cost of $40. I can not explain the difference between the $16 and the $40, but a substantial part of the difference between the $40 and $100 is a difference between those who know that their overdrafts will be paid and those who believe that their overdrafts will be bounced.

The difference in perceived cost between one time overdrafters and multiple time overdrafters may raise questions about my definition of those with knowledge and those without.

In the preceding analysis, I have defined customers who overdrafted in the past as behaving with full information and those who have never overdrafted as behaving under the assumption that the depository will bounce any overdrafts. I test this definition and find that those who have never overdrafted maintain larger precautionary balances. The problem in testing this contention is the reverse causality. More cautious people would hold larger precautionary balances and therefore overdraft less. However, when I control for this added caution, I still find that those who have never overdrafted hold higher balances.

I control for accountholders' relative levels of caution by including in the linear regression the incidence of past overdrafts. To the extent that the level of past overdraft will be a result of low precautionary balances, the coefficient on this will be negative. Then the effect which shows up solely on having no overdrafts is due to the information difference.

Table 5: **Effect of Knowledge**

Model:	(1)		(2)	
	Coef	Std Err	Coef	Std Err
Constant	9.35**	0.197	9.35**	0.197
Never Overdrafted	0.112**	0.035	0.118*	0.044
One or No Overdrafts			−.011	0.046
ln Past Overdrafts	−.038**	0.010	−.039**	0.011
(ln Past Overdrafts)^2	0.007*	0.004	0.007*	0.004
ln Transacton Balances	0.261**	0.017	0.928**	0.017
ln Pay Period	−.032	0.025	−.031	0.025
Overdraft in Sample	−.028	0.038	−.027	0.038
Overdrafts/Pay Periods	−.835**	0.107	−.833**	0.107
Adjusted R^2	0.2919		0.2916	
No. of Observations	1950		1950	

Significant at: *95%, **99%
Note: Dependent Variable is ln Precautionary Balance

If the relationship between *log of past overdrafts* and precautionary balances is not linear but exhibits convexity then this might show up as a positive coefficient on *Never Overdrafted*. Therefore, in column (1) of Table (5), I include the *square of the log of past overdrafts* to account for the convexity. The square is indeed positive and significant indicating the convexity is present, but the coefficient on *ever overdrafted* is still negative and significant. So even when I account for the convexity in the curve, we still see a difference in precautionary balance holding between those who have never overdrafted and those who have.

In column (2), I include an indicator variable for those with only one overdraft in the past. These people are also very cautious about their checking account balance but made one mistake. There should be very little difference between those who have overdrafted once and those who never overdrafted. However, the coefficient on *Never Overdrafted* is still significant. Again, this indicates that those with the knowledge that this institution pays most overdrafts hold a lower precautionary balance.

6. Public Policy Implications

In January 2003, the Federal Reserve collected 350 comments concerning bounce protection programs as they consider how or if they should regulate. At issue is whether regulators should classify bounce protection programs as loans and thus subject them to *Truth in Lending* requirements. The language of legislation and regulation has the most to say about whether bounce protection programs should be regulated as loans or as depository account features but two economic issues are relevant.

Suggested regulations range from banning them to requiring disclosure of an APR. The Federal Reserve has not moved to end bounce protection but several courts and state regulators have taken positions which are more critical of bounce protection. While the interpretation of current regulations is a legal matter, the intent of the original laws and regulations is an economic one. Whether bounce protection programs fit the legal definition of an "extension of credit" or fit the philosophical definition of credit is for others to argue. I ask whether consumers are using overdrafts to obtain credit and find that 35% of overdrafts are acting like loans and the other 65% are unintentional mishaps of checking accounts.

When an accountholder overdrafts, either he knows that he is doing so or does not realize that the check will overdraft. Most accountholders do not know the exact checking account balance when they write checks. They do not know when previous checks will clear or when exactly their directly deposited paycheck will be posted to their accounts. This uncertainty leads to situations where checks which are intended to clear instead overdraft. Accidental overdrafting is not a substitute for a loan – it is a substitute for a bounced check – so regulators should question whether these overdrafts should be regulated like loans.

In other cases, people knowingly overdraft. This is a felony if they expect the check to bounce. However, with the new bounce protection programs, even though most depositories reserve the right to bounce or pay the checks at their discretion, consumers count on the overdraft being paid by the depository and giving them time to bring their accounts to a positive balance in the future. In other words, they are consciously spending now, money which they will not have until the future. A payday loan is a better substitute for this kind of overdraft so it should be regulated consistently with other forms of credit.

Whether bounce protection programs should be regulated by Truth in Lending or by Truth in Savings is an empirical question. Are overdrafts primarily mistakes or are they

Table 6: **Distribution of P(.)**

	With credit card rate		With savings account rate		Only Savings accountholders[a]		Log-Linear Logit Estimation	
	Estimated	Actual	Estimated	Actual	Estimated	Actual	Estimated	Actual
Percentile[b]:								
10th	.043	0	.039	0	.015	0	.0004	
25th	.045	0	.041	0	.016	0	.005	
Median	.059	0	.055	0	.020	0	.022	
75th	.074	0	.068	0	.026	0	.051	
90th	.113	.248	.105	.248	.038	.23	.094	
Max	.249	1	.250	1	.076	1	1.00	
Mean[b]	.070 (.000028)	.07	.064 (.000088)	.07	.024 (.0110)	.06	.041 (.0085)	.063
Fit	.871		.875		.901		.917	
Obs	1950	1950	1949	1950	123	124	1950	1950
Total Overdrafts			1362.2	1331 (35.7)	33.6	109 (6.9)	858.8	1321 (28.7)
Difference			– 31.2		75.3**		462.2**	
Obs			21284		1401		20946	

Significant at: *95%, **99%
Note: Standard Errors in (Parentheses)
[a]Sample is restricted to those accountholders with savings accounts.
[b]Calcualted from fitted values of regressions reported in Tables (3) and (4)

intentional? Certainly both motivations exist but how much of each? In section (5) above, I use two methods to estimate $P(B_P)$, the probability of bouncing a check unintentionally, given the precautionary account balance held. The model of section (3) is clearly a model of unintentional overdrafting so the estimation in model (2) is unintentional overdrafting.

Model (4) is also a model of unintentional overdrafting thought it is a little less obvious. Model (4) is a simple reduced form estimation of overdrafting on several factors. If I were to estimation that model using the whole data set, intentional and unintentional overdrafts I would get parameter values which reflect both types of overdrafting. However, if I use a data sample which is populated by people who overdraft only unintentionally I would have parameter values – and therefore a reduced form model – which reflects unintentional overdrafting. This is what I do. I restrict the sample in model (4) to only those accountholders who have a history of overdrafting fewer than once a month. Then when I calculate fitted values for *P(.)* for all 1950 accounts, I get the probability of unintentionally bouncing, even for those out of sample observations – those with a history of frequent overdrafts.

Therefore, given B_P, the two models eash imply a number of unintentional bounces. The rest are intentional. The structural method does not perform well, but the direct estimation says that 35% of overdrafts are intentional.

The structural method relies on the assumptions implicit in equation (2), that B_P is set optimally given r and it assumes a functional form, but makes no implicit judgement as to which overdrafts are intentional and which are not. In fact, the number of overdrafts did not enter into the estimation. The strength of this methodology is that the researcher does not have to look at each overdraft and judge whether or not it was intentional. The weakness is that it relies on a functional form first and the data second.

The larger problem, though, is that the median expected probability of overdrafting ones account is 6.4% and ranges from 4% to 10% in the 10^{th} and 90^{th} percentiles. This means that the median accountholder should accidentally overdraft more than once out of every 20 pay periods. This implies more overdrafts than are actually seen in the current sample. Standard errors are calculated on the probability of overdrafting using the delta method. The probability of overdrafting is specified as the PDF of a logistic distribution. Using the delta method the variance of $P(\beta|x)$ is:

$$\frac{1}{N}\left[\frac{e^{x\beta}\left(1-e^{x\beta}\right)}{\left(1+e^{x\beta}\right)^{3}}\right]x'\Sigma x\left[\frac{e^{x\beta}\left(1-e^{x\beta}\right)}{\left(1+e^{x\beta}\right)^{3}}\right]$$

where Σ is the variance-covariance matrix for the coefficients on the variables (x) in *P(.)*. This yields a standard error for each individual. The average across individuals is .000088. The Ben-Akiva/Lerman (1985) measure of fit is reported.

The goal is to segregate the intentional overdrafts from the mistakes. Remember that *P(.)* was defined in section (3) to be the probability of unintentionally overdrafting. The basic strategy is to compare expected to actual overdrafts.

This expected probability (.064)[7] is the mean of one Bernoulli trial. The incidence of several overdrafts follows a binomial distribution. Given this expected probability of overdrafting, we would expect to see 1362.2 overdrafts in a sample of 21284 person pay periods.

In this sample, we observe 1331 overdrafts, not statistically different from the predicted amount. However, a casual glance at the data and conversations with the data providers are quite convincing; intentional overdrafting does exist . Therefore, the model's prediction of no intentional overdrafts is another reason to question the accuracy of the structural model.

Looking at the direct estimation of *P(.)*, 858.8 overdrafts are predicted but actual

[7] As a simplification, I use the mean probability of bouncing rather than each accountholder's individual probability. In order to calculate the true expected number of overdrafts where each individual has his own probability of overdrafting, we would need to use the product of the probabilities of overdrafting (or not overdrafting) for each individual over each possible combination of joint overdrafts/not-overdrafts. This is intractable, but applying the fitted probability of overdrafting for the mean individual to each individual yields a binomial distribution and the problem is quite tractable.

overdrafts total 1321. This means that 35% of overdrafts can be classified as intentional.

7. CONCLUSION

This paper uses account statement data from one depository institution to separate the incidence of honest mistakes from intentional overdrafts. One aim of this paper is to provide regulators with a better understanding of consumers' experience with bounce protection programs in order to learn more about consumer and banking behavior before regulations of bounce protection are implemented. The paper finds that 35% of overdrafts are intentional and the rest are honest mistakes. Given that the distribution of overdrafts across customers is unequal (i.e. few customer write most overdraft) this 35% of overdrafts is most likely written by a much smaller portion of the customer base. Whether these results argue for regulation under Reg Z or Reg B I will let others decide, but they will now have the data to inform their decision.

The bounce protection program reduces the costs of overdrafting for account holders. As the cost of overdrafting declines, consumers hold lower account balances, offering themselves less protection against unintentional overdrafts – lower *precautionary balances*. The Baumol-Tobin (1952 and 1956) model of cash holding forms the basis for the econometric model used to examine consumer behavior. In the model, accountholders choose their levels of precautionary balances so that the marginal cost of holding precautionary balances (the loss of interest) equals the marginal benefit (from the reduction in the likelihood of overdrafting). This first order condition is then used as a structural model in the estimation.

I also estimate a reduced form equation regressing observed overdrafts on precautionary balances and personal characteristics. The reduced form estimates are more believable than the structural estimation. The structural estimation cost of overdrafting is implausibly low and the model predicts that all overdrafts are inadvertent. In contrast, the reduced form estimation gives more credible results. The model does not capture consumers' demand for checking account balances as well as a simple reduced form estimation does. These results indicate that the Baumol-Tobin (and successor) framework is not very useful for determining checking account allocations. Finding a replacement model of checking account allocation is an area for future research.

One possible direction for this future research is a two stage game where in the first stage customers choose whether or not to have overdraft protection while the second stage is represented by the section (3) model. A model of heterogeneous customers might help to determine if a portion of the population is hurt by bounce protection. This paper is a first step in understand customer's checking account balance holding. Clearly, more work is needed to fully understand this asset allocation decision.