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ADOPTION OF FINANCIAL TECHNOLOGIES: IMPLICATIONS FOR MONEY DEMAND AND MONETARY POLICY

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ABSTRACT

In this paper we argue that the relevant decision for the majority of US households is not the fraction of assets to be held in interest bearing form, but whether to hold any of such assets at all (we call this "the decision to adopt" the financial technology). We show that the key variable governing the adoption decision is the product of the interest rate times the total amount of assets. The implication is that, instead of studying money demand using time series and looking at historical interest rate variations, we can look at a cross-section of households and analyze variations in the amount of assets held. We can use this methodology to estimate the interest elasticity of money demand at interest rates close to zero.

We find that (a) the elasticity of money demand is very small when the interest rate is small, (b) the probability that a household holds any amount of interest bearing assets is positively related to the level of financial assets, and (c) the cost of adopting financial technologies is positively related to age and negatively related to the level of education. The finding that the elasticity is very small for interest rates below 5 percent suggests that the welfare costs of inflation are small.

We also find that at interest rates of 6 percent, the elasticity is close to 0.5. We find that roughly one half of this elasticity can be attributed to the Baumol-Tobin or intensive margin and half of it can be attributed to the new adopters or extensive margin. The intensive margin is less important at lower interest rates and more important at higher interest rates.

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I. Introduction

How does inflation distort household behavior? A common answer to this question is given by Allais (1947), Baumol (1952) and Tobin's (1956) inventory analysis. According to the story, during periods of high inflation, consumers increase the number of financial transactions ("trips to the bank") so as to hold more of their purchasing power in the form of interest bearing assets and less in the form of money.[1] The key of the model is that agents are able and do substitute money for interest bearing assets so as to minimize the total cost of asset management. This may be a good model of how households manage currency holdings - although little evidence is available on this point - but it may not be a useful model of household demand deposit ownership. The reason is that, for the story to work, households need to be able to substitute between money and alternative assets that yield a superior return. The problem is that the majority of households in the United States do not hold financial assets other than checking accounts. In Table 1, for example, we use data on asset holdings of U.S. households as measured by the 1989 survey of consumer finances (SCF). We see that 59 percent of total U.S. households do not hold any interest bearing assets and 53 percent of those who hold checking accounts, do not hold any interest bearing assets.[2] Hence, if we think of checking accounts as monetary assets (as most economists do when they think of M1 as money

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[1] There are alternative theories of money demand. For example Sidrauski (1967 a, b) introduces money in the utility function so inflation distorts the relative price between money and the other consumption goods and affects utility. Another example is the model of transactions demand for cash of Karni (1973), Kimbrough (1986), and McCallum and Goodfriend's (1987). In this theory, inflation leads people to use more time carrying out transactions because the use of monetary assets (which are required to reduce the need to carry out such transactions) is optimally reduced.

[2] The 59 percent of households who do not hold any interest bearing assets hold 23 percent of the monetary assets (checking and savings accounts) in the United States, even though they hold only 4 percent of total financial assets.

supply), then a straightforward interpretation of Baumol-Tobin's inventory theory of money demand cannot be applied, at least not for the majority of households.

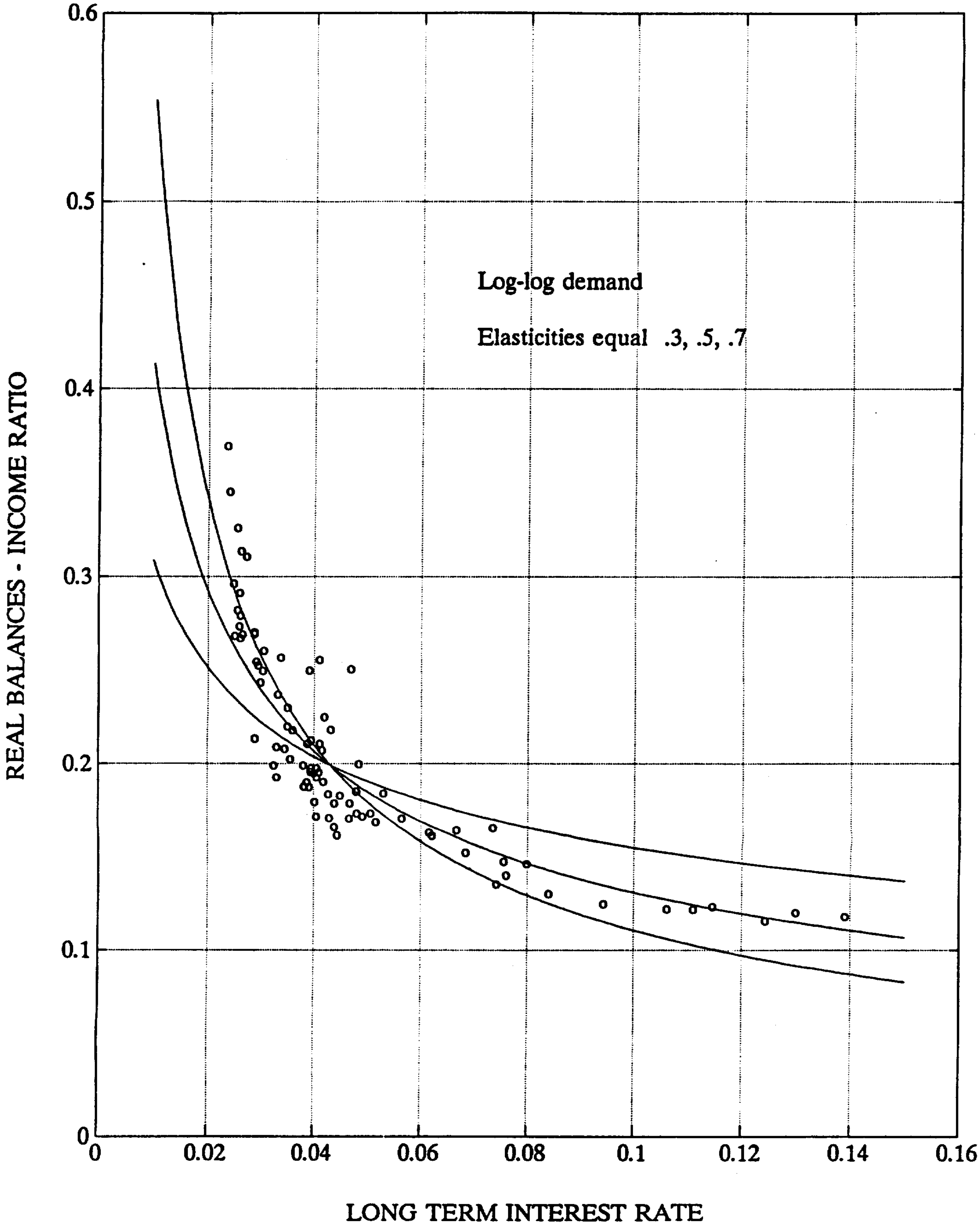
The question is why don't all these people hold any interest bearing assets. One possible explanation is that there might be an initial setup cost before these assets can be used. For example, it may be costly to learn about how they work or there may be a fixed cost of managing them (in fact, the fixed management cost may be the reason why financial institutions supply these assets in minimum-sized bundles.) The key point is that, in order to use these assets, households need to "*adopt the technology*" and this adoption is *costly*.[3] In this paper we build a model of this discrete decision and we estimate it using U.S. household data from the SCF. We show that, as predicted by our model, a household's likelihood of purchasing interest bearing assets depends on the quantity of their financial wealth. We also find that college educated people more readily purchase interest bearing financial assets.

The realization that the adoption decision is important has a major implication: it allows us to estimate the interest elasticity of household money demand at very small interest rates. We feel that this is an interesting contribution of the paper because all of the analyses of social costs of inflation are based on "out of sample" estimates of the interest elasticities of money demand. For example, following Bailey (1956), Lucas (1994) uses the constant elasticity function $M^d = y \cdot A \cdot R^{-\eta}$, (where y is the level of income, A is a constant, and η is the constant interest rate elasticity) and

[3] An alternative explanation for the existence of 59 percent of households with no interest bearing assets can be found in the traditional Baumol-Tobin inventory model when the integer constraints are taken into account: households who have no interest bearing assets are those who optimally chose to "go to the bank" less than once. Under this interpretation, one could say that the contribution of this paper is the theoretical and empirical exploration of the implications of this first integer constraint.

estimates that the welfare cost of U.S. inflation is about 1% of GDP. His basic methodology consists of integrating under a money demand function as depicted in Figure 1 (which has been taken from Lucas (1994).)

FIGURE 1: U.S. MONEY DEMAND, 1900-1985



(Source: Lucas (1994))

One of the things we can infer from Figure 1 is that a substantial fraction of the welfare cost of having a 6 percent interest rate comes from the area under the money demand function associated with values of the interest rate close to zero. However, and this can also be seen in Figure 1, the U.S. nominal interest rate has never been near zero[4]. It follows that, in order to estimate the cost of inflation, one must extrapolate people's behavior when interest rates are very low, from observed behavior at moderate and high interest rates. In his preferred empirical specification, Lucas's extrapolation implies that the largest behavioral changes - and therefore the largest marginal deadweight losses - occur at the lowest nominal interest rates (his preferred specification is the constant interest elasticity money demand function with elasticity 0.5. Of the three money demand functions depicted in Figure 1, Lucas chooses the one in the middle.)

Note that if one argued that, instead of shooting up to infinity, the money demand function was almost horizontal when R was close to zero, then the measured welfare costs of inflation would be a lot smaller. And the lack of data points near zero would make this conjecture as plausible as any other. Hence, the true cost of inflation remains an open issue, and will remain so until we get good estimates of the elasticity of money demand at interest rates near zero. Measuring this elasticity is one of our goals in this paper.[5]

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[4] The possible exception is the WWII period. In Figure 1, the smallest interest rates observed correspond to this exceptional period. The degree of confidence we can put on this war interest rates is, to say the least, limited.

[5] As Lucas notes in his paper, the measured welfare cost of inflation critically hinges on the interest rate elasticity at low interest rates. For example, he experiments with the money demand function $M^d = y \cdot B \cdot e^{-\xi \cdot R}$, where B and ξ are constants. The interest rate elasticity for this alternative function is equal to $\xi \cdot R$. Note that this elasticity goes to zero as R goes to zero, and it increases with R. When Lucas uses this alternative demand function, the welfare costs drop from the one percent of GDP mentioned above to 0.3 percent of GDP. He prefers the constant elasticity formulation because of its superior fit on U.S. aggregate time-series data. Such data,

In order to estimate the elasticity of money demand at low interest rates, we start by arguing that the decision to adopt a financial technology is an important one. By the decision to adopt we mean the decision to pay the fixed cost of learning about or managing interest bearing assets. In our model, therefore, households have to decide whether to adopt the financial technology before they choose how much of their wealth to hold in interest bearing form and how much in the form of money. The interest elasticity of money demand, therefore, depends on two different margins: the *"intensive margin"* of switching between money and interest bearing assets for people who use interest bearing assets regularly (this the traditional Baumol-Tobin effect) and the *"extensive margin"* resulting from changes in the fraction of people who choose to adopt interest bearing financial technologies.[6,7]

The nominal interest rate affects the extensive margin because it is part of the benefit of adopting the financial technology: the higher the interest rate, the larger the incentive people will have to adopt it. The key point is that the interest rate, R, affects the decision to adopt in the same way as does the quantity of financial assets, A. The intuition for this is that the benefit of adopting the financial technology is the total interest generated by the assets held in that form. This total

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however, do not include many (or any) observations of low nominal interest rates.

[6] We should note that, when the interest rates are small, the significant margin is the extensive one because when interest rates are close zero, the gains of adopting are small so few households will have adopted.

[7] Barro (1970) also models the adoption of financial technologies and studies the implications of his model for the interest elasticity of money demand. He estimates the parameters of his model with time series data on hyperinflations. Hence, he focuses on the interest rate elasticity at very large values of R whereas we estimate the same at very small interest rates. We also depart from Barro by showing how the interest elasticity can be estimated from cross-sectional data and by emphasizing the implications of our results for the welfare cost of inflation.

interest, in turn, is the product of the interest rate, R, times the amount of assets, A. For example, the gain to the consumer is close to zero if the product R·A is zero, independent of whether the product is zero because R=0 (why adopt if the interest rate differential is negligible?) or because A=0 (why adopt if he has no assets to protect against inflation?). Hence, consumer behavior will be similar when A is very small and when R is very small. This means that if we want to analyze household behavior when the interest rate is very close to zero (that is, when their losses from not adopting are small), we can investigate how the people with low amount of assets behave even if interest rates are not close to zero because these are the people whose losses from not adopting are small. In other words, *given that the analysis of time-series evidence is bound to give NO information on the elasticity of money demand near zero, we can find out about this interest rate elasticity by looking at a cross-section of households and analyzing the behavior of the households with small amounts of assets.* If we conclude that people do not change their behavior when their assets increase from 10 dollars to 100 dollars to 1,000 dollars to 5,000 dollars, if we see that a substantial fraction on of people are willing to have 5,000 dollars in the form of money (or checking accounts) before they decide to use interest bearing assets, then we will see that people are willing to accept substantial interest losses before they decide to start using interest bearing assets. We will in this case say that people do not react much to changes in the interest rates when the interest rates are close to zero so the interest elasticity of money demand is small. In sum, by taking advantage of the symmetry between R and A we are able to forecast the interest sensitivity of money demand for interest rates that are outside of U.S. historical experience.

Our model also has strong refutable implications. We test the hypothesis that A and R affect the adoption decision symmetrically and we are unable to reject it. We also predict that the interest elasticity is practically zero for very low interest rates, 0.5 for moderate interest rates, and around one for very high interest rates. The intuition for finding very small elasticities for small interest rates is that, on one hand, when the interest rates are small, most people will not use interest bearing assets. On the other hand, the marginal change in the number of adopters is small when the interest rates are low (as it will be shown in Section III). Hence, the change in aggregate behavior will be small. This is a very strong prediction which could be refuted by the data. Finally, we are able to use the empirical estimates of the model to study how much of the interest sensitivity of money demand can be attributed the *"intensive margin"* and how much to the *"extensive margin"*. To advance the main result on this point, we find that the interest elasticity of household checking account demand is about 0.5. Of this overall elasticity we attribute a bit less than one half to the traditional intensive margin and a bit more than one half to the extensive margin.

The rest of the paper is organized as follows. In Section II we present a simple static model that highlights the main points of our argument. In Section III we describe the data sets from the 1989 and 1983 Survey of Consumer Finances. Section IV presents the estimates of the simple probit when a constant fraction of interest bearing assets is assumed. We use these estimates to compute the interest rate elasticity of household money demand derived from the adoption decision. In Section V we amend the theory and we allow households to hold different fractions of their wealth in interest bearing form, depending on their level of wealth and interest rates. Section VI presents the Tobit estimates of the more general model. In Section VII we decompose the overall interest rate elasticity into a Baumol-Tobin component (or intensive margin) and an adoption component (or extensive margin). Section VIII introduces dynamic elements which are estimated in Section IX. The final Section concludes.

II. A Static Model of the Adoption of Financial Technologies

II.A Setup

Consumers must decide whether or not to hold some of their financial assets in interest bearing form. Let A_i denote consumer i's financial assets - including non-interest bearing demand deposits and interest bearing assets such as money market accounts, bonds, stocks, CDS, or mutual fund shares. The benefit of interest bearing assets is the interest earned. In any period, a household must pay a fixed cost in order make use of these interest bearing assets. If and when household i has already decided to pay the cost and to use the financial technology, then he holds a fraction of his overall financial assets in interest bearing form. In this section we assume that this fraction, which we label α_i, is the same for all households so $\alpha_i=\alpha$. In other words, we start with a model where, once the financial technology has been adopted, households do not play the Baumol-Tobin game and they keep a constant fraction of their wealth in interest bearing form. We relax this assumption in Section V.[8]

Let R_i denote the interest differential between "interest bearing" financial assets and "monetary" assets such as demand deposits.[9] Holding constant the quantity of financial assets, the

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[8] It should be intuitively clear that this assumption is quite innocuous when we focus our attention to the behavior of money demand at low interest rates: when R is close to zero, then nobody holds interest bearing assets. Hence, whether changes in R lead to large, small or no changes in α is of little importance.

[9] We think that the interest rate differential between interest bearing financial assets and monetary assets is proportional to the nominal interest rate on interest bearing assets: Let R_R be the interest rate paid to interest bearing assets (equal to the real interest rate plus the expected inflation rate) and R_m the interest paid to monetary assets. We imagine that a fraction, λ, of the monetary deposits, D, held by banks needs to be held (for legal or technological reasons) in the form of reserve cash. The rest is lent at the rate R_R. Thus, banks pay a total of $R_m \cdot D$ in interest to monetary accounts and receive a total of $(1-\lambda)\cdot D \cdot R_R$ dollars from lending. If there is free entry into the business of offering monetary accounts, there will be no profits from these operations so

gain to consumer i of using the financial technology is the product $R_i \cdot \alpha \cdot A_i$. This is because, by definition, no interest can be earned on financial assets unless the financial technology is adopted.

We suppose that there are two types of costs to adopting the financial technology. The first is a fixed cost ψ which is incurred every period that the technology is used, regardless of the intensity of the use of the technology (ie, independent of the quantity of financial assets that are held in interest bearing form). This cost depends on a vector of household characteristics such as age, schooling, or the distance from the nearest financial institution. The second is a variable cost which is proportional to the quantity of assets held in interest bearing form. This could be, for example, a proportional fee charged by the broker. We subsume this variable cost in the interest rate differential R.

II.B. Optimal Adoption

Interest-bearing assets will be used by household i with characteristics X_i when the benefits, $R_i \cdot \alpha_i . A_i$, exceed the cost $\psi_i(X_i)$. Hence, he will adopt if

$$R_i \cdot \alpha \cdot A_i > \psi_i (X_i) \tag{1}$$

Because our basic model has no startup costs,[10] the decision to hold some interest bearing assets at age t depends only on A, ψ, α, and R. Lagged variables do not affect the decision. It

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the equality $R_m \cdot D=(1-\lambda) \cdot D \cdot R_R$ will hold. This zero profit condition can be rewritten as $R_R - R_m = \lambda \cdot R_R$. It follows that the interest rate differential, $R \equiv R_R - R_m$, is proportional to the nominal interest rate R_R.

[10] We will deal with dynamic considerations and startup costs in Sections VIII and IX.

doesn't matter whether A was expected to follow the life cycle path that it followed ex post.[11]

II.C. Cost Heterogeneity

We allow for the possibility that the fixed costs, ψ_i, vary across consumers. We allow it to vary with age and schooling, as well as with other characteristics such as distance between home and the relevant financial institution, the health condition of the members of the household, or whether the head of the family is retired or not. For example, older and less educated people may have less (or perhaps more) ability to adopt financial technologies, and less healthy people may find it more costly to engage in financial transactions. Costs are also allowed to have an idiosyncratic component.

$$\ln\psi_i(X_i) = \beta_{i,0} + \beta \cdot X_i \qquad \textit{with} \qquad (\beta_{i,0} - \mu)/\sigma \sim \Phi, \tag{2}$$

where the vector X_i reflects the relationship of costs with age and schooling and perhaps other characteristics on the cost of adoption. The coefficient $\beta_{i,0}$ is the person-specific component of the cost, which is independent of asset holdings, A_i, and household characteristics, X_i. The variable $(\beta_{i,0} - \mu)/\sigma$ is distributed according to the cumulative distribution function Φ, which we will assume in our empirical work to be the standard normal. The parameters μ and σ can be interpreted as the mean

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[11] It can be argued that the reason why a lot of people do not hold interest bearing assets is that these assets are offered in "minimum-sized bundles". In other words, one cannot purchase a 20 cent certificate of deposit. Presumably, banks require these minimum deposit amounts because they face a fixed cost. Hence, households hold interest-bearing assets if $A > A_{min}$, where A_{min} is the minimum deposit requirement. Banks, in turn, choose A_{min} knowing that they face a fixed cost of managing these accounts. Let us denote the fixed cost by faced by bank j by ϵ_j. A zero profit condition for the marginal accounts will ensure that the benefits, which are an increasing function of the revenue generated by these accounts, $R \cdot A_{min}$, are equal to the costs, ϵ_j. That is, $f(R \cdot A_{min}) = \epsilon_j$. By inverting $f(\cdot)$ we get $R \cdot A_{min} = f^{-1}(\epsilon_j \equiv \psi_j$. This condition ensures that households hold interest-bearing assets if $A \cdot R > \psi_j$. Note the similarity between this, and condition (1).

and standard deviation of $\beta_{i,0}$.

The probability that household i with financial assets A_i is holding interest bearing assets is:

$$\text{Prob}[\ R_i \cdot \alpha \cdot A_i \ > \ \psi_i(X_i)\ ] \ =$$

$$\text{Prob}[\ \beta_{i,0} \ < \ \ln A_i + \ln R_i + \ln \alpha_i - \beta \cdot X_i\ ] \ =$$

$$\Phi\left(\frac{\ln A_i + \ln R_i + \ln \alpha_i - \beta X_i - \mu}{\sigma} \right) \tag{3}$$

If we consider a population of households, each of which has assets A, and characteristics X (and we assumed that α is the same for each of these households), then the fraction which hold interest bearing assets is:

$$d(R|A,X) = \Phi\left(\frac{\ln A + \ln R + \ln \alpha - \beta X - \mu}{\sigma} \right) \tag{4}$$

where Φ is the cumulative distribution function for the cost parameter β_0. Note that $d(R|A,X)$ increases monotonically in R - more people use interest bearing assets when the interest differential is higher.

Equation (3) illustrates an interesting feature of the model: holding constant α, the interest rate and the quantity of assets have the *same* effect on the adoption of the financial technology. A household with assets A/2 but facing an interest rate of 2R will, according to the model, make the same adoption decisions as a household with assets A and facing an interest rate of R. This allows us to use the cross-sectional data to make inferences about the behavior of households in economies with very high (low) interest rates by looking at the behavior households with very high (low) financial asset holdings. We believe this is an important advantage over time series studies which only provide information about monetary behavior over range of interest rates that were experienced over the time period being studied.

II.D. The Demand for Money and its Interest Elasticity

The average money demand from the household sector is the weighted sum of the demand of adopters and non-adopters, where the weights are the fraction of households who adopt and the fraction who don't respectively. The demand for money by non-adopters is A, while the demand by adopters is $[1-\alpha]$A. Since the fraction of the population that has adopted is given by $\Phi(\cdot)$ and the fraction that has not adopted by $1-\Phi(\cdot)$, the average demand for money by people with assets A, and characteristics X is given by:

$$\begin{aligned} l(R|A,X) &= [1 - \Phi(\cdot)]A + \Phi(\cdot)[1-\alpha]A \\ &= A\left[1 - \alpha\Phi\left(\frac{\ln A + \ln R + \ln\alpha - \beta X - \mu}{\sigma}\right)\right] \end{aligned} \qquad \textbf{(5)}$$

If we graph this money demand as a function of the interest rate, we will note that its shape is similar to the inverse of the shape of a cumulative distribution function, as displayed in Figure 2. For low values of R, it is almost horizontal, it falls rapidly for intermediate values of R, and it asymptotes zero for large values of R.

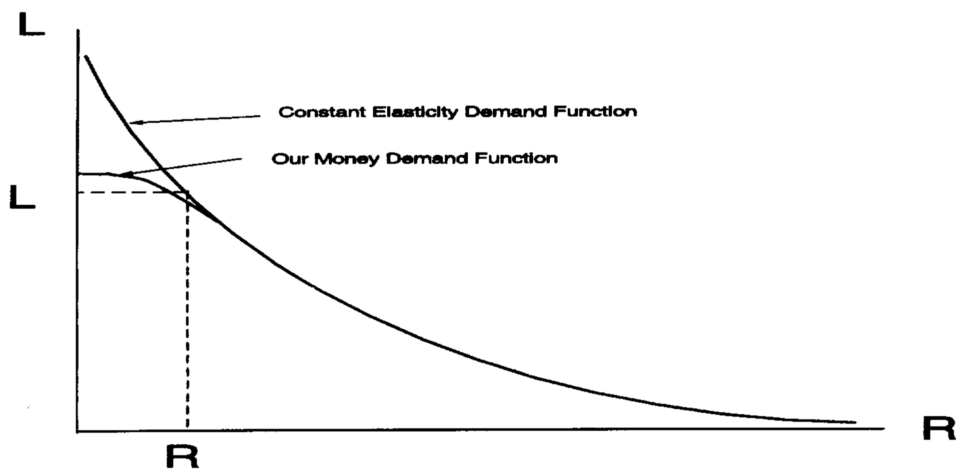

Figure 2: The shape of the money demand function.

By taking the derivative of the log of this money demand function with respect the log of the interest rate, we get that the interest rate elasticity for this group is:

$$\begin{aligned}\varepsilon(R|A,X) &= -\frac{A}{l(R|A,X)}\frac{\alpha}{\sigma}\phi\left(\frac{\ln A + \ln R + \ln\alpha - \beta X - \mu}{\sigma}\right)\\ &= -\frac{1}{1-\alpha\, d(R|A,X)}\frac{\alpha}{\sigma}\phi\left(\Phi^{-1}[d(R|A,X)]\right)\end{aligned} \tag{6}$$

The first term above, $1/(1-\alpha d)$, is monotonically increasing in R. It reflects the ratio of average A to average money holdings. As R approaches zero, this term approaches 1. As R approaches infinity, this term approaches $1/(1-\alpha)>1$. The second term, $\alpha\phi(\Phi^{-1}[d])$, reflects the change in the fraction of adopters, Φ, that arise from a small increase in the interest rate. Remember that ϕ is the density function corresponding to the cumulative distribution function Φ. When plotted against R, the term

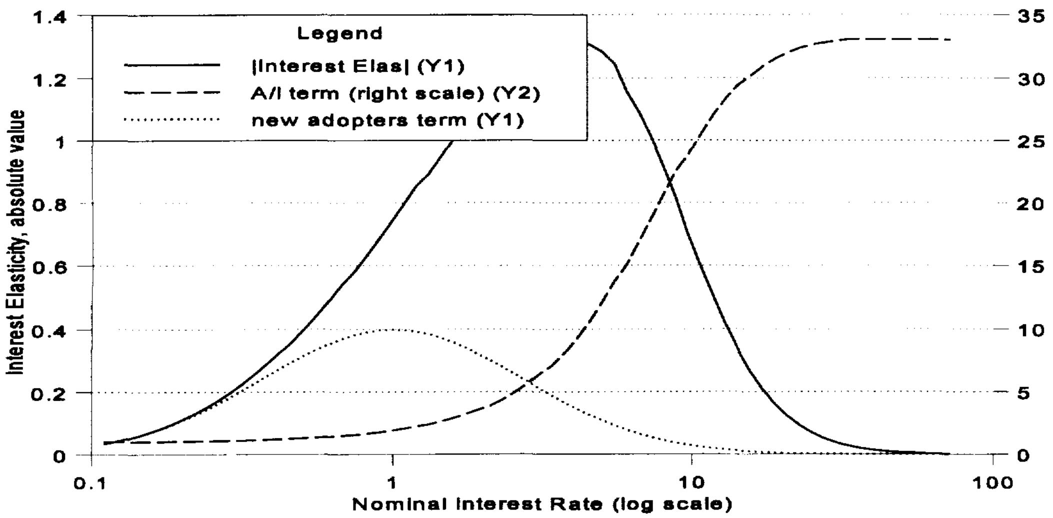

Figure 3: Interest Elasticity of Money Demand

follows the shape of the density function for the cost term β_0, which is hill shaped for unimodal distributions. The maximum is attained at the mode which, for a normal distribution Φ, occurs at $\ln R = \beta \cdot X + \mu - \ln A - \ln \alpha$. For very small and very large values of R, this term approaches zero. These two terms, together with their product the interest elasticity, are graphed below for the case of a unimodal distribution.

The magnitudes above are hypothetical and will change with changes in the parameters of the model, but the shapes are not particular to the parameters shown. The interest elasticity is basically a hill-shaped function of R, with its greatest magnitude at a nominal interest rate greater than $\ln R = \beta \cdot X + \mu - \ln A - \ln \alpha$ (which is shown as 1 in the figure above).[12] The interest elasticity approaches zero as R becomes very large or very small.[13] This is because for large (small) R almost everybody (nobody) has adopted so there is little behavioral change as a result of increasing (decreasing) R any more.

We also see that the interest elasticity is a hill-shaped function of assets. Hence, a prediction of the model is that, if governments tax money according to its interest elasticity (e.g., for Ramsey considerations), then the nominal interest rates will follow a u-shaped pattern with economic development. Very poor and very rich economies will have high nominal interest rates. Middle economies - where middle is defined to be an economy where roughly half of the households have adopted - will have the lowest nominal interest rates.

III. Data from the Survey of Consumer Finances

We estimate the parameters of our model with data from the 1989 SCF. We measure the variable A as the dollar value of financial assets held by the household. These assets include checking accounts, money market accounts, savings accounts, savings bonds, CDS, other bonds, mutual fund

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[12]There can be multiple peaks of the interest elasticity as a function of R, but the single peaked case seems to prevail for the parameters that we have tried.

[13]This figure has been parameterized so that scale of the horizontal axis corresponds to annual percentage points. So a 1 on the graph represents a nominal interest rate of 1% per year, a 10 represents 10 percent per year and so on. Thus, according to the parameters that we have chosen, the hill-shaped relation between interest rates and elasticities will occur for reasonable values of the interest rate. We estimate these parameters in later sections of the paper.

shares, and equities. We think of "interest bearing assets" as those assets which pay a relatively high rate of return and are somewhat substitutable for money - money market accounts, CDS, other bonds, mutual fund shares, and equities. We define an adopter of the financial technology to be a household which has a positive quantity of any of these "interest bearing" assets.[14]

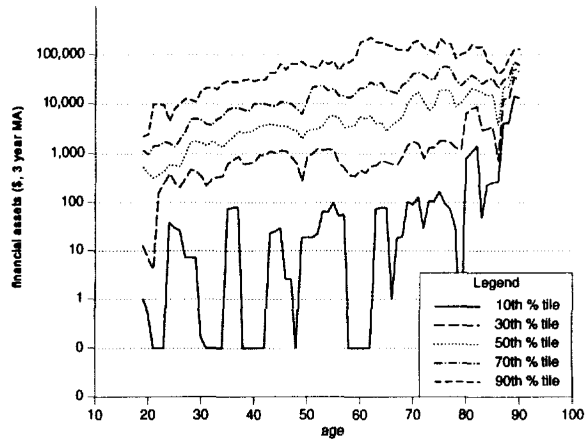

Figure 4 Distribution of Financial Assets by Age

Figure 4 displays the 10th, 30th, 50th, 70th, and 90th percentiles of the financial asset distribution for each age group.[15] We see that assets rise with age: median financial asset holdings rise from $500 in the early twenties to $20,000 in the late seventies.[16]

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[14]Pension and "social security" wealth are excluded because they entail little adoption costs as they are usually provided by the firm with little effort on the part of the worker or household.

[15]Because we have relatively few sample households for any particular year of birth (e.g.., we have 40 29-year-olds, 63 47-year-olds, and 41 71-year-olds), we compute our statistics for each birth year and then display a weighted three year moving average in the figure. The weights are the number of sample observations for the corresponding birth year.

[16]The y-axis is a log scale. The jagged pattern for the 10th percentile appears in the figure because, for several age groups, more than 10% of households report zero financial assets.

We have argued that households with $R\alpha A$ greater than the cost, ψ, should have adopted. Suppose, for example, that the cost $\psi = R\alpha 2000$ and that x% of age group t has more than 2000 in financial assets. Then we predict that x% of that age group should have adopted. Figure 5 graphs Centiles of the financial asset distribution corresponding to four dollar amounts: \$1000, \$2000, \$3000, and \$4000. If the cost $\psi/\alpha R$ is constant across age groups, then, by the reasoning above, we

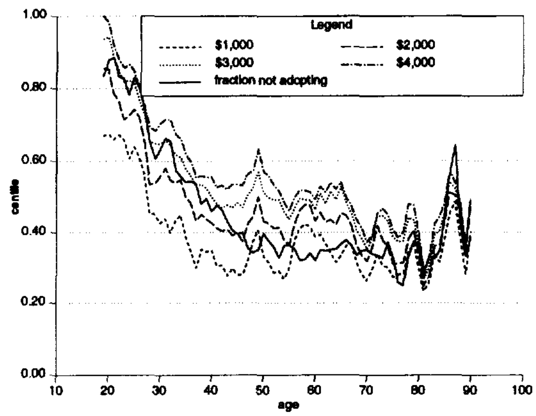

Figure 5 Centiles of the Financial Asset Distribution for four dollar amounts and fraction of non-adopters

predict that the fraction of nonadopters should coincide with the centiles corresponding to $\psi/\alpha R$ dollars in financial assets.

Figure 5 also displays the fraction of non-adopters for each age group. We note that the fraction falls from more than 80 % of households in their 20s to close to 50% for households between 30 and 40 to close to 40% for households in their 50s. The fraction of nonadopters is fairly constant after that age. Figure 5 shows two important properties of the data set. First, the decision to adopt seems to follow a life-cycle pattern Second, the fraction of non-adopters follows the centiles corresponding to the dollar amounts between \$1000 and \$4000. This suggests that the cost term $\psi(\cdot)$

is between αR1000 and αR4000. For α≈ 1 and R = 0.05, this implies an annual cost of between $200 and $800. If the cost of using interest bearing assets were 10 or 40 hours per year and the value of time were about $20/hour, Figure 5 suggests that household's decisions to purchase interest bearing assets are rational.

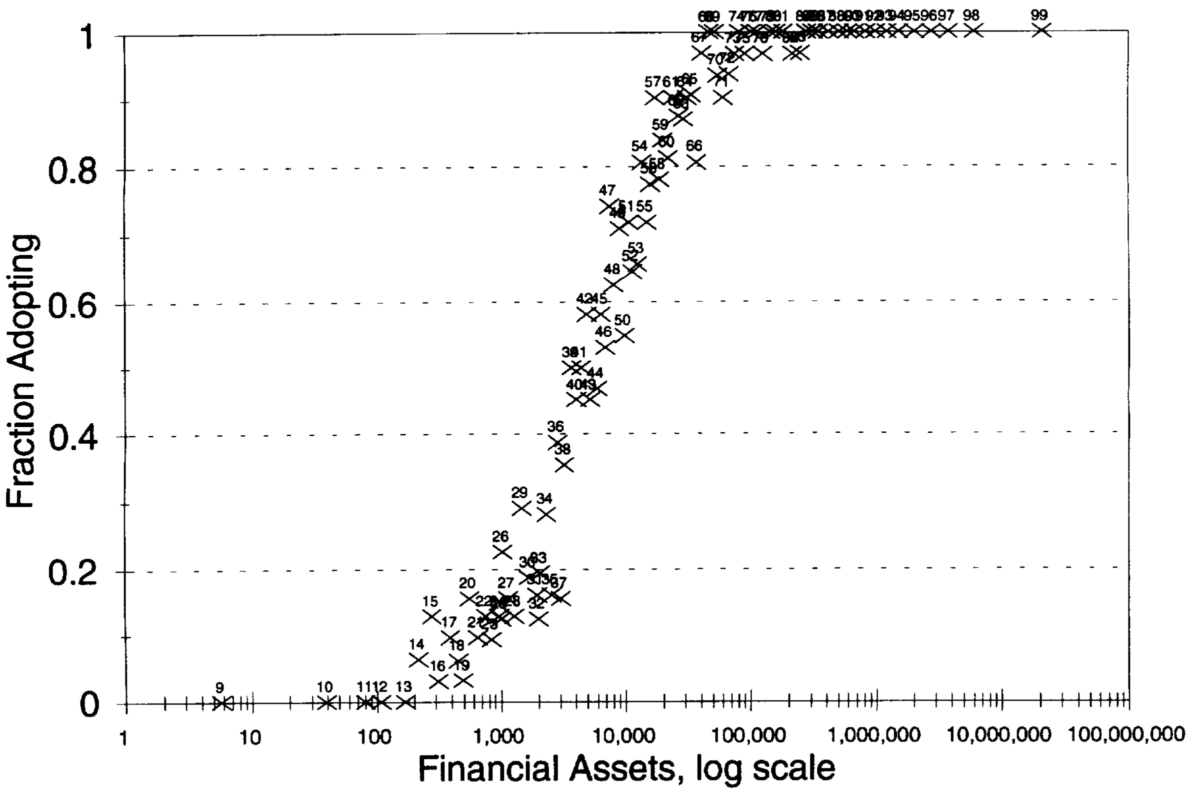

Figure 6 Fraction Adopting vs. Financial Assets
(NOTE: Each point graphs a centile mean. Centiles are unweighted and of size 31 or 32)

In Figure 6 we plot the fraction of household that adopt the financial technology versus the amount of financial assets they own. Each point in the figure represents the mean of a centile of the financial asset distribution, with each centile containing roughly 31 households. We see that the fraction of adopters is nil for the first 13 centiles. This suggests that a proportional change in the level of assets (and, therefore, a proportional change in the benefits of adoption) when the level of assets is small triggers a small, almost negligible, change in the fraction of households who adopt. The same is true at the highest levels of assets: a proportional change in the level of assets for rich households triggers no change in the fraction of adopters.

In this paper we will also use the asset data of the 1983 Survey of Consumer Finances. The reason is that in a later section we will argue for the need of lagged values of A as an instrument for A. We will also introduce dynamic elements to our model which will require the use of lagged values of A as an additional explanatory variable in the probit estimates. Given that, of the 2847 households that participated in the 1989 survey, 1343 also participated in the 1983 survey, we can use this smaller sample in order to have household data at two points in time. We can therefore use the 1983 values of a variable as a lagged value of its 1989 counterpart.

IV. Probit Estimates of the Static Model with Constant α.

Table 2 displays probit estimates of equation (1) using the 1989 Public Use Cross-Section of the Survey of Consumer Finances. Column (1) has the log of financial assets as the sole explanatory variable. The coefficient on ln A is 0.661 (s.e.=0.022). Thus, the logarithm of financial assets is a key explanatory variable for the probability of adoption of a financial technology. Under the assumptions that Φ is the standard normal distribution, that the costs are not a function of X ($\beta = 0$), and that α is independent of financial assets, the coefficient on ln A is a consistent estimate of

$1/\sigma$[17] so we estimate σ=1/0.661= 1.51. Column (2) adds age and a dummy for college as explanatory variables. Although the coefficient on age is negative (indicating that old people are less likely to adopt) it is not statistically significant. The coefficient on college is positive and significant: people with a college degree are more likely to adopt.[18] The introduction of these two variables does not alter the coefficient on ln A much.[19]

Since we lack data for household-specific interest rates, we cannot in principle introduce the interest rate, R, in our empirical analysis. However, if we assume that all households face the same pre-tax interest rate differential (or that they face an interest rate that is uncorrelated with other explanatory variables) we can use the marginal tax rate faced by each of the households to proxy for the rate of return. The reason is that the relevant interest rate for the decision adopt, however, is the interest rate differential *net of taxes.* We therefore compute the marginal tax rate for each family using data on household income and using the 1989 income tax code and use the following interest rate:

$$\ln R_i \cdot (1-\tau_i) = \ln R_i + \ln(1-\tau_i) \tag{7}$$

,

where τ_i is household's i marginal income tax rate. Under the assumption of lack of correlation with other explanatory variables, the term ln R_i will disappear into the error term and the term $\ln(1-\tau_i)$ will

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[17]In Section V, we allow for α to be a function of (A*R). In this case, the probit coefficient on ln A is no longer an estimate of $1/\sigma$, but the coefficient enters the computation of the interest elasticity in the same way as $1/\sigma$.

[18] We tried years of schooling instead of the college dummy. It never enters with a statistically significant coefficient. We therefore report only the college dummy specifications.

[19]We have experimented with non-linear terms for age, but they were not significant. Hence, we dropped them from the analysis.

capture the variation in the relevant interest rate differential.

Column (3) implements this idea empirically by estimating the same probit with the log of $1-\tau_i$ as an additional explanatory variable. The coefficient on ln A is similar to the ones we estimated before, 0.666 (s.e.=0.025), and the coefficient on college is positive and significant, 0.168 (s.e.=0.079). The new element is that the coefficient on $\ln(1-\tau_i)$ is 0.471 (s.e.=0.414). The test of the hypothesis of identical coefficients for ln A and $\ln(1-\tau)$ cannot be rejected at the usual levels of significance.

Column (4) introduces the log of household income as an additional explanatory variable. It fails to be significant. Columns (5) introduces the *distance* of the home from a financial institution. The rationale for this variable is that having the financial institutions could contribute to the cost of adopting technology (if the costs were related to some kind of physical transportation). This variable enters negatively (the farther away the financial institution is from the home, the less likely it is for the household to adopt) but fails to matter significantly. Column (6) introduces a dummy variable for poor health, which tries to capture the fact that a poor health may increase the costs of adopting a financial technology. The variable is negative but not significant. Column (7) introduces a dummy variable for retired people. The reason is that retired people may have more time to manage their money and, as a result, they may confront a lower adaptation cost. We find that retired people are less likely to adopt, although this is not significant.

Instrumental Variables

The probit estimates presented in Table 2 are subject to two types of potential problems. First, financial assets may be measured with error. This means that differences across households in the level of financial assets are partly the result of measurement error so we should not expect to see a large behavioral response to a change in measured A even when the true behavioral response is large. Second, A may respond to unobserved components of the cost (ψ) or benefits (R) of adoption. For example, some households may face a rate of return on financial assets that is relatively high when compared to the rate of return they face on nonfinancial assets such as their home or business. This would encourage them to hold financial assets and, holding constant A, to adopt the financial technology. A solution to both of these problems is to use instrumental variables. We propose some instruments that are correlated with A but that we believe are uncorrelated with unobserved components of ψ or R and uncorrelated with measurement errors. These instruments are a *lagged value of A* and an *age polynomial.* The correlation between age and A is 0.29. The correlation between the value of A in 1989 and its corresponding 1983 value is 0.89.

Table 3 reports the instrumental-variables probit estimates which are suggested by our model in the case that α is independent of R. Column (1) reports the results of the instrumental variables estimation when only an age cubic polynomial is used as a predictor of $\ln A_{1989}$. The coefficient on $\ln A_{1989}$ declines slightly to 0.35 (s.e.=0.02) but remains positive and strongly significant.[20]

The next two columns use the 1983 as well as the 1989 SCF. In order to establish comparability, in Column (2) we reestimate a probit without instrumental variables, but with the sample of households that appear in both the surveys. Note that the sample size of the panel members is 1342 rather than the 2847 households available for the 1989 survey. The coefficient on $\ln A_{1989}$ is, 0.722 (s.e.=0.040), which slightly larger than the 0.67 we got for the full 1989 sample. When ln

[20] If we include a linear age term in the second stage, the point estimate on ln A is very similar. The confidence interval on ln A grows because age is the main predictor of ln A in the first stage.

A_{1983} is included as an instrument for ln A_{1989} (reported in Column (3)) the estimated coefficient on ln A_{1989} is 0.58 (s.e.=0.03), similar to that we estimate without instruments. Again, the coefficient is slightly smaller but still significantly positive. The main message of the instrumental variables estimation is, therefore, that the probit estimate of 0.67 might be slightly biased upwards because of simultaneity bias. This bias, however, does not seem to be the main story behind the positive point estimate.

Finally, see in Table 3 that the point estimates on college and ln(1-τ) are more sensitive, although we cannot reject the hypothesis that the coefficient on ln A_{1989} and ln(1-τ) are the same.

Empirical Findings on Money Demand and its Interest Elasticity

We use the regression coefficient from Table 2 and equation (6) to compute the interest elasticity for each financial asset decile of our sample. We repeat the formula for the interest elasticity for convenience:

$$\varepsilon(R|A,X) = -\frac{1}{1-\alpha\, d(RA|X)}\frac{\alpha}{\sigma}\phi\left(\Phi^{-1}[d(RA|X)]\right)$$

Our calculations presume that the vector $\beta = 0$ and that α is constant. Using our estimate of 0.66 for $1/\sigma$ from Table 2, we graph in Figure 7 the interest elasticity as a function of financial assets.

Two methods of calculation are used. The "restricted" method, whose results are displayed as a solid line, assumes that that α is independent of financial assets and that d(RA) varies with RA according to the normal distribution as implied by the theory. In this calculation, α is set to its sample median value of 0.8. The "unrestricted" method, for each financial asset centile, uses the centile mean of α and the centile fraction adopting to allow d(RA) and α to vary with financial assets in a "nonparametric" way. The two methods yield similar computations.

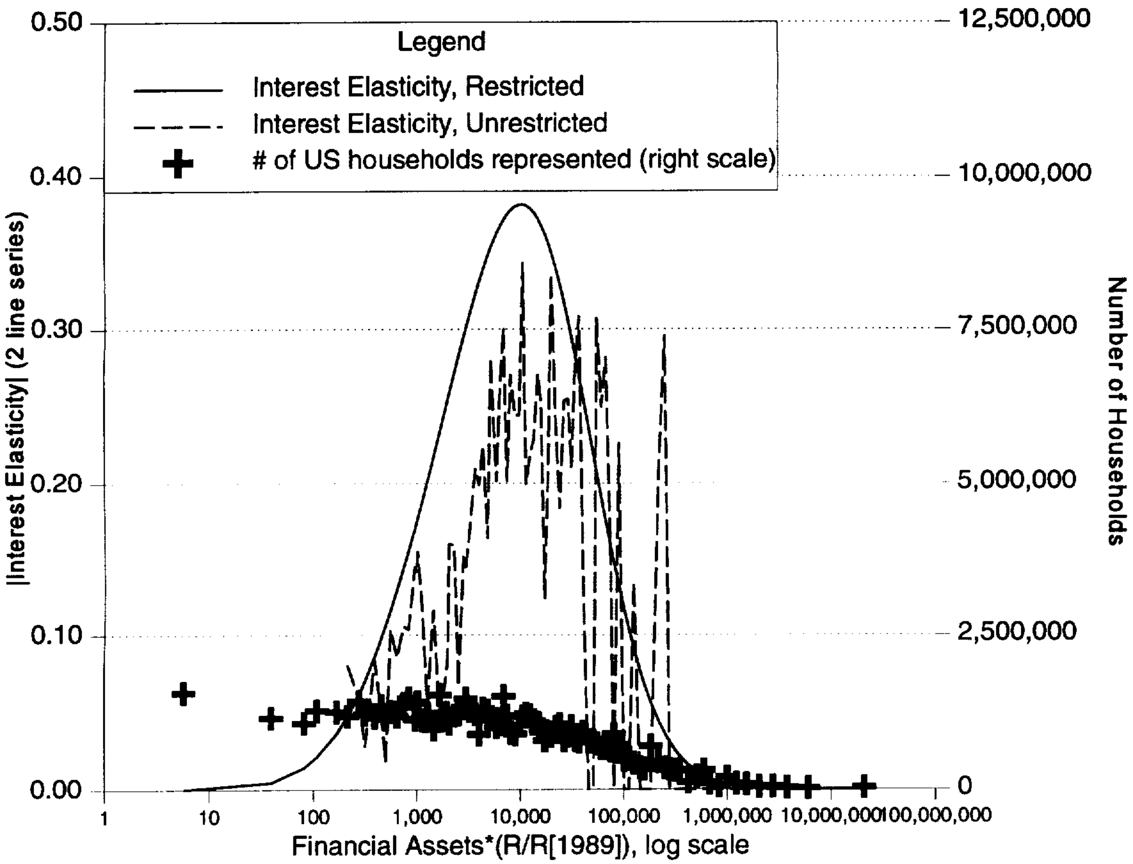

Figure 7 Estimate Interest Elasticities

Each data point is constructed from roughly 30 sample households. The crosses indicate the number of U.S. households that are represented by each data point.[21] We see that the bulk of U.S. households have between $1,000 and $100,000 in financial assets, so the interest elasticity relevant

[21] 14% of U.S. households are not represented because their sample counterparts (9% of the sample) report zero financial assets.

for most households is between 0.1 and 0.3. The mean interest elasticity is .13 (.19 for restricted version).

The horizontal axis is labeled "Financial Assets*(R/R_{1989})." Notice that A and R enter our model symmetrically so Figure 7 can also be interpreted as a graph of the interest elasticity versus the nominal interest rate. Because one tick on the horizontal axis represents a factor of ten, an increase in the nominal interest rate by a factor of ten would shift the entire figure to the left by one tick. Consider, for example, a person with $1,000 in financial assets in real terms. Let's hold fixed this person's real financial assets and change the nominal interest rate. His elasticity would fall for lower nominal interest rates. It would increase up to a point for higher nominal interest rates and then, after roughly a factor of 10 increase in the nominal interest rate, begin to decrease.

V. Endogeneizing α.

V.A. Setup.

We have assumed up to now that, once they have adopted, households hold a constant fraction, α, of their assets in interest bearing form. We want to relax now this assumption by assuming that, conditional on holding interest-bearing assets, the fraction held in interest-bearing form depends on the quantity of assets and on the interest rate. We settle on a functional form for this dependence by supposing that the demand for money is given by:

$$M^d = \begin{cases} (1-\nu)A + \nu A\, L(A,R) & \text{if adopt} \\ A & \text{if not} \end{cases} \qquad (9)$$

where ν represents an idiosyncratic component of the demand for money. The function L(A,R) takes values between zero and one. We expect this function to be decreasing in R.

The variable ν is assumed to be log-normally distributed, which implies that M^d can be negative. As in Tobin's (1958) analysis of automobile purchases, we assume that a negative M^d means that the consumer holds no money and that he will not hold positive amounts without inframarginal changes in his demand:

$$M = \begin{cases} M^d & \text{if } M^d > 0 \\ 0 & \text{if } M^d \leq 0 \end{cases} \tag{10}$$

According to our definition of $\alpha \equiv 1 - (M^d/A)$,

$$\ln \alpha \equiv \begin{cases} 0 & \text{if adopt } \& \ M^d \leq 0 \\ \ln \nu + \ln[1 - L(A,R)] & \text{if adopt } \& \ M^d > 0 \\ \text{unobserved} & \text{if not adopt} \end{cases} \tag{11}$$

We show the three possible cases above. In the first case, the consumer has adopted the financial technology but he holds no money so the econometrician does not observe his desired money demand. In the second case, the consumer has adopted and desired money demand is observed. In the third case, the consumer has not adopted so ln α cannot be observed.[22]

V.B Costs and Optimal Adoption

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[22]We neglect the case where no financial assets of any kind are held.

Interest-bearing assets will be used by household i when the benefits, $R \cdot \alpha_i A \cdot_i$, exceed the cost $\psi_i(X)$:

$$\text{adopt if: } R \cdot \alpha_i . A_i > \psi_i(X)$$

As in Section II, the cost of adoption varies with household characteristics such as age and schooling:

$$\ln \psi_i(X) = \beta_{i,0} + \beta \cdot X \tag{12}$$

with

$$(\beta_0, \ln v) \sim N\left(\begin{bmatrix} \mu_\beta \\ \mu_v \end{bmatrix}, \begin{bmatrix} \sigma_\beta^2 & \rho \sigma_\beta \sigma_v \\ \rho \sigma_\beta \sigma_v & \sigma_v^2 \end{bmatrix} \right) \tag{13}$$

The idiosyncratic cost $\beta_{i,0}$ and the money demand parameter v are jointly independent of asset holdings A, and X. $\beta_{i,0}$ and $\ln v$ are distributed according to a bivariate normal distribution.

The probability that household i with financial assets A_i is holding interest bearing assets is:

$$\text{Prob}[\, R \cdot \alpha_i . A_i > \psi_i(X) \,] =$$

$$\text{Prob}[\, \beta_{i,0} - \ln v_i < \ln A_i + \ln R + \ln [1 - L(A_i, R)] - \beta \cdot X \,] =$$

$$\Phi\left(\frac{\ln A_i + \ln R + \ln [1 - L(A_i, R)] - \beta X - \mu}{\sigma} \right)$$
$$\mu \equiv \mu_\beta - \mu_v$$
$$\sigma \equiv \sqrt{\sigma_\beta^2 + \sigma_v^2 - 2 \rho \sigma_\beta \sigma_v} \tag{14}$$

If we consider a population of households, each of which has characteristics *X* and has assets A, then the fraction d(R | A,*X*) which hold interest bearing assets is:

$$d(R|A,X) = \Phi\left(\frac{\ln A + \ln R + \ln[1 - L(A,R)] - \beta X - \mu}{\sigma}\right) \quad \textbf{(15)}$$

In our empirical analysis we use the following functional form for L(·):

$$L(A,R) = \frac{\delta A^{\eta-1} R^{-\gamma}}{1 + \delta A^{\eta-1} R^{-\gamma}} \quad \textbf{(16)}$$

V.C A Tobit Model of ln A.

Equation 11 and the cost specification of the last section deliver a model for ln α:

$$\ln\alpha = \begin{cases} 0 & \text{if } \ln\nu \geq \ln\psi - \ln A - \ln R - \ln[1 - L(A,R)] \ \& \ \ln\nu \geq -\ln[1 - L(A,R)] \\ \ln[1 - L(A,R)] + \ln\nu & \text{if } \ln\nu \geq \ln\psi - \ln A - \ln R - \ln[1 - L(A,R)] \ \& \ \ln\nu < -\ln[1 - L(A,R)] \\ \text{unobserved} & \text{if } \ln\nu < \ln\psi - \ln A - \ln R - \ln[1 - L(A,R)] \end{cases} \quad \textbf{(17)}$$

This is a very close cousin of the Tobit model with some differences:

(i) The truncation rule depends on the independent variable (ln A)
(ii) The model is nonlinear in the parameters (because L(A,R) must be in (0,1))
(iii) It requires the numerical integration of bivariate normal.

Item (i) is not a big problem - several popular statistics packages, such as STATA, include this extension as part of their Tobit routine. Item (ii) requires a slight modification of the likelihood function used by STATA and other packages to compute linear Tobits. See the Appendix for the likelihood functions that we use.

Other than brute force quadrature, item (iii) can be handled in to ways. First, we can ignore truncation at $\ln \alpha = 0$, assuming that $M^d=0$ at this point rather than $M^d \leq 0$. This may be an efficient shortcut because less than 5% cases have $\ln \alpha = 0$. Another solution is to set $\rho = 0$.[23]

V.D. The Demand for Money and its Interest Elasticity.

Average money holdings are now given by

$$l(R|A,\alpha,X) = [1 - \Phi(\cdot)]A + \Phi(\cdot)[1-\alpha]A$$
$$= A\left[1 - \alpha\,\Phi\!\left(\frac{\ln A + \ln R + \ln\alpha - \beta X - \mu}{\sigma}\right)\right] \tag{18}$$

If we take the derivative of $\ln l(\cdot)$ with respect to ln R we find the interest elasticity of money demand:

$$\varepsilon(R|A,X) =$$
$$-\frac{1}{1-\alpha(R,A)\,d(R|A,X)}\left[\frac{\alpha(R,A) + [1-\alpha(R,A)]\,\gamma\,\alpha(R,A)}{\sigma}\,\phi\big(\Phi^{-1}[d(R|A,X)]\big) - d(R|A,X)\,\gamma\,\alpha(R,A)[1-\alpha(R,A)]\right] \tag{19}$$

[23] In the first case where the $\alpha = 1$ corner is ignored, we estimate $\rho \approx 0$ so the assumption of $\rho = 0$ may not be so bad.

It is worth comparing this expression for the interest elasticity with Eq. 6, derived under the assumption of a constant α. The α/σ term corresponds to the previous elasticity. This term just reflects the direct effect of the rate of interest on adoptions. The second term in the numerator is an indirect effect of R on adoptions through changes in α. The final term derives from the change in the money demand of non-marginal adopters. Notice that the first two terms involve marginal adopters and therefore they involve the density function ϕ. These two terms go to zero as R becomes very large or very small. The final term approaches zero for small R because almost nobody adopts at low R so that sensitivity of α to R is largely irrelevant. For large R, however, almost everybody adopts. The final term approaches 0 as R approaches infinity.[24]

VI. "Tobit" Estimates.

We now use the "Tobit" model to jointly estimate the parameters governing the adoption decision and the parameters governing the quantity of money demanded conditional on adoption. The results are reported in Table 4. The first four rows of the Table report the estimates of the coefficients of he adoption equation. Columns (1) and (2) do not restrict the coefficients on ln A, $\ln(1-\tau)$ and $\ln(1-L(\cdot))$ to be the same, as predicted by the model. We estimate that the effect of ln A on adoption is quite similar to our probit estimates - the "Tobit" estimates are 0.66 or 0.67 as

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[24]The limit of this final term depends somewhat on functional forms. For values of ν different from one, this elasticity will go to zero as long as $L(\cdot)$ tends to zero when R goes to infinity, and the limit elasticity of L() with respect to R is finite. When ν takes the value of one, however, this elasticity tends to $-\gamma$.

Because $\gamma\alpha(A,R)$ represents the elasticity of L(A,R) with respect to R, readers can easily think about the case where $\gamma\alpha(A,R)$ is constant as R approaches infinity: one can see from the equation that $\epsilon(R)$ will approach this constant.

compared to probit estimates of 0.67. We find this similarity because ln A has only a small (although statistically significant) effect on the fraction of assets that adopters hold in their checking accounts and because the fraction has a small effect on the probability of adoption. The coefficient on age is not significant and the college dummy is positive and statistically significant. In the third column we restrict the coefficients to be the same. We estimate a value of 0.59 (s.e.=0.02) which, again, is not very different from the estimates found in our simple probits. The null hypothesis that the coefficients on ln A, ln(1-τ), and ln(1-L(A,R)) are equal cannot be rejected at the 95% confidence level.

The sixth and seventh rows of Table 4 report the estimates of the effects of ln A and ln(1-τ) on the fraction of assets hold in their checking accounts. When we exclude ln(1-τ) from the analysis (Column 1), we find that the coefficient on ln A is -0.17 (s.e.=0.05). The introduction of ln(1-τ) in the estimation reduces the coefficient of ln A to -0.24 (s.e.=0.05), while the coefficient on ln(1-τ) is -1.55 (s.e.=0.53). The two coefficients change little when the estimation is restricted (see Column 3). Hence, we conclude that the interest rate has sizeable effects on the fraction of assets that adopters hold in their checking accounts.

A possible interpretation of the negative effect of ln R (as measured by ln (1-τ)) is that ln (1-τ) is proxying for the level of income. One could argue that a good measure of the number of transactions (which is the variable that belongs in the money demand function according to Baumol-Tobin) is the level of income. If we exclude income and include its marginal tax rate, the latter will capture the effects of the former. In Column (4) we include the log of income as an additional explanatory variable for the adopter's money demand function, and find that it has a positive sign, although it is insignificant (0.03, s.e.=0.03). The variable ln(1-τ), on the other hand, remains negative and significant, although the point estimate declines slightly. The coefficient on ln A changes little.

VII. Decomposing the overall Elasticity into intensive-margin and extensive-margin components.

We now want to say whether the behavioral response to changes interest rates will tend to arise from the intensive or extensive margins. The theory suggests that, when the product AR is low, adoption is rare so any behavioral change in response to a change in R must come mainly from marginal adopters (even if the adopters change their behavior substantially, their effect on aggregate behavior will be small since they are few). When AR is high, on the other hand, most people have adopted so their behavior will be an important determinant of aggregate behavior (and these are the people who might be behaving according to the inventory model). In this section we decompose the aggregate money demand elasticity at empirically interesting levels of A and R into marginal adoptions and the behavioral change of adopters.

In order to decompose the overall elasticity into an intensive margin component and an extensive margin component, we need to settle on a value of γ. Given that our empirical estimates do not pin down γ with much precision, we will adopt an alternative strategy. We will consider four values of γ. We use γ=0 (the case corresponding to a constant α), γ=0.5 (which roughly corresponds to the Baumol-Tobin model[25]), γ=1 (which is a reasonable intermediate value) and γ=2 (which we consider to be an upper bound of the true γ). For each of the values we use Equation (19) to compute the elasticity associated with all interest rates between 0.1% and 1000%. Equation (19) requires a value for σ and α. Our empirical estimates indicate that $1/\sigma$=0.6. We set α to its

[25] This correspondence is not exact because the functional forms are different. The Baumol-Tobin money demand function exhibits a constant interest elasticity at 0.5 while our functional form does not.

median sample value of 0.8. Finally, we choose a benchmark value for d(R): when R=5%, we assume the household has a 50% adoption probability. Figure 8 displays the resulting elasticities. It also displays the fraction of adopters corresponding to the case $\gamma = 0$.

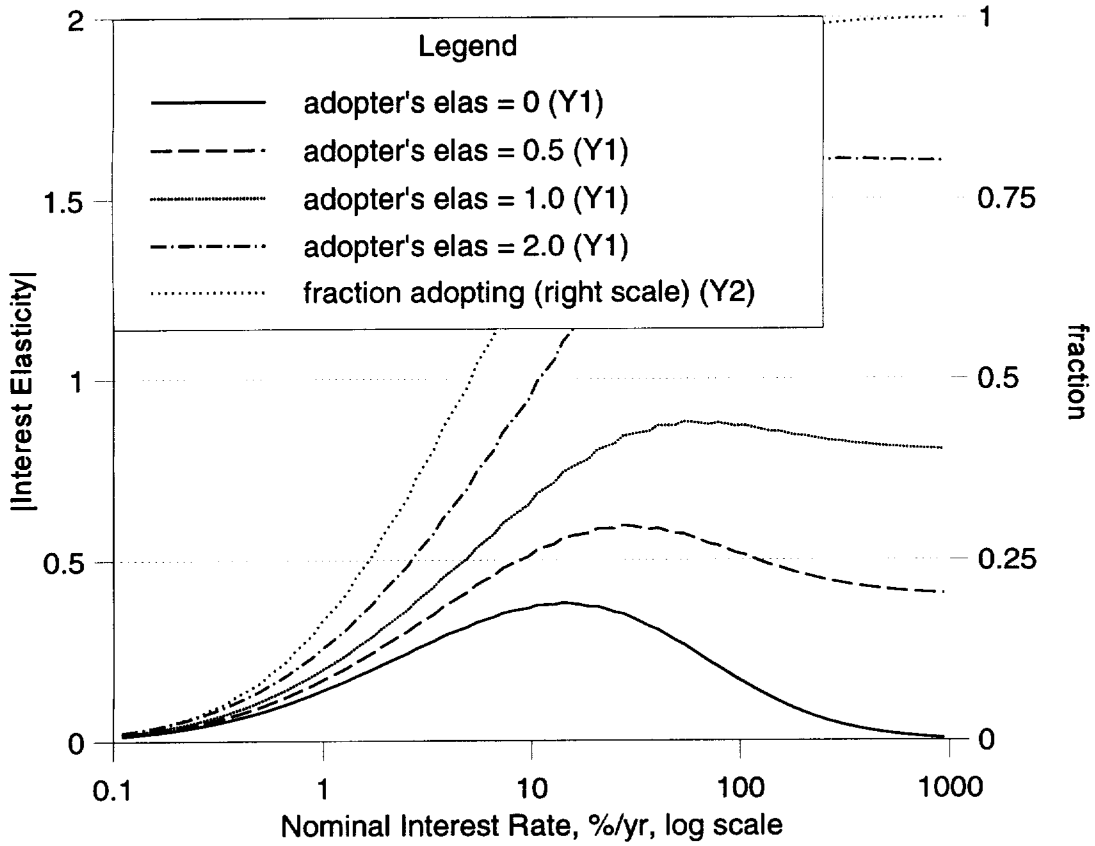

Figure 8 Interest Elasticity as a function of the Nominal Interest Rate in the model with endogenous α.

If there is no behavioral response to an interest rate change conditional on adopting (that is, if γ=0), then all of the aggregate response is from changes in the decision to adopt so all the elasticity comes from the extensive margin. We see from the solid line that the aggregate household money demand elasticity is about 0.3 at a 5% interest rate and increases to about 0.4 at about a 15% interest rate. The elasticity falls for larger interest rates. The dotted line displays the fraction of households that have adopted for every interest rate when $\gamma=0$.

The lines corresponding to higher values of γ show that, even if γ is as large as 2 our predictions for the money demand elasticity are not so different for interest rates less than 20%/yr. For higher interest rates, a sizable fraction of people adopt and the aggregate elasticity is a combination of the elasticity of adopters and that resulting from marginal adoptions. Our estimates are therefore more sensitive to γ at these higher interest rates.

To decompose the overall elasticity between an extensive and an intensive margin, pick one of the values of γ, say $\gamma=1$. Consider a 5% annual interest rate. The curve representing $\gamma=1$ suggests that, at this interest rate, the overall elasticity is 0.5. The curve representing $\gamma=0$ suggests an elasticity of 0.3. That is, if there were no intensive margin the elasticity would be $\epsilon=0.3$ but, in actuality it is $\epsilon=0.5$. Hence, we say that the overall interest rate elasticity of money demand is 0.5 and a bit more than one half of it is due to extensive margins.

VIII. Introducing Dynamic Elements.

The models of sections II and V were static in the sense that, at a point in time, everybody is assumed to be able to pay a yearly cost and gain access to the financial technology. This assumption seems inappropriate if the cost of adoption entails a startup component. For example, an important component of the cost of adoption could be the "learning" that needs to take place before one can use financial assets. This learning process is probably done once. Once learned, the technology can be used without having to pay any further learning costs (this assumes no technological *innovations* in the financial sector which need to be learned).

When startup costs are important, new elements enter our analysis. For example, conditional on assets, the young will be more likely to have adopted because they had a longer horizon when the technology was introduced (or became cheap). This is a reason to expect a negative effect of age on the likelihood of having adopted a new technology even when the cost of adoption is independent of age. Non-monotonic lifetime profiles for assets introduce another effect of age on the probability of adoption: for a given level of current assets, older people are more likely to have experienced a high level of assets in the past. For this reason, we might expect age to be positively affect the probability of adoption. Uncertainty about future asset holdings introduces another positive age effect. This is because an additional term will in the equation (1) determining the optimal age of adoption - a term which reflects the option value of waiting to adopt. The magnitude of the option value will depend on the variance of future asset holdings and on the magnitude of future interest which might be earned. We expect this option value of waiting to decline with age as there are fewer years to be uncertain about.

Because financial asset holdings - and therefore the benefits of adopting - grow with age in our data, we expect that there is not a strong incentive to "unadopt" the technology in order to avoid the annual fixed cost ψ, for a given interest rate R. On the other hand, in a data set where, for example, nominal interest rates have fallen substantially over time, we may expect to see households who have paid the startup cost but who are not currently using the technology.

To see the potential importance of startup costs, in Table 5A we report the fraction of households that hold interest-bearing assets in 1983 and 1989. In 1983, 58.2 % of the households did hold interest bearing assets and 41.8% did not.[26] The corresponding numbers for 1989 were 60% and 40%. A total of 50.4% of the sample held interest bearing-assets in both years while 32.3% did not hold assets in either year. The interesting figure is that 13.4% of the households (115 out of 860) who owned interest bearing assets in 1983 did not hold such assets in 1989. In other words, a significant fraction of households "dropped" the financial technology between 1983 and 1989. A possible explanation is, of course, that interest rates were much lower in 1989 than they were in 1983. The benefits of using financial technologies were much lower so a substantial fraction of the population decided not to use them, even though the startup costs had already been paid in 1983. This finding suggests that, regardless of whether start up costs are important, the fact that so many households stop using the financial technologies means that the yearly adoption costs (as we modeled them in the first part of the paper) are empirically important.

Nevertheless, in this section we will introduce startup costs into our analysis. We conjecture that, in the presence of such costs, the likelihood of adopting depends on "permanent" level of assets, $\ln A^*$, which we measure as a weighted average of current and past log assets:

$$\Phi\left(\frac{\ln A_t^* + \ln R + \ln \alpha - \beta X - \mu}{\sigma} \right) \qquad \ln A_t^* \equiv \lambda \ln A_t + (1 - \lambda) \ln A_{t-1} \tag{20}$$

This specification allows for assets to decline with age, but assumes that, holding constant age, the

[26] These figures are unweighted because we do not have the sample weights for 1983. Hence, 50.4% of the households in the sample hold assets in both periods. We don't know what fraction of the United States households these represent.

whole path of past assets is summarized by ln A_{t-1}. Any other characteristics of the past path which affect the likelihood of having adopted by age t are assumed to be uncorrelated with the other variables of interest. The basic idea is that, holding constant current assets, households with high assets in the past are more likely to have adopted. This effect arises because the high past level of assets before generated enough extra interest to justify undertaking the startup cost and because relatively high past assets suggest that the household's current level of assets may be temporarily low.

The parameter λ will be large when asset holdings are very persistent. In the limiting case where assets are independently distributed at each moment in time, λ will be quite small because current assets say little about the lifetime benefits of adopting. The parameter λ will also depend on the size of the startup cost relative to the other costs. For relatively small startup costs, decision rules will approximate those under the static model and λ will be close to 1. For large startup costs, lagged assets will have an important effect on the current likelihood of having adopted.

IX. Estimates of the Dynamic Model

In Section VIII we showed that the key to the dynamic aspects of the model was to estimate the probit with ln A_{t-1} as an explanatory variable. In practice, we can implement this idea by using ln A_{1983} as the lagged value of ln A_{1989}. The results are reported in Table 6. Column (1) estimates the probability of adoption in 1983 by using ln A, age and a college dummy as the only explanatory variables. The sample of households used in this regression is the panel of 1343 households who participate both in the 1983 and 1989 surveys. The first thing we note is that the coefficient on ln A is 0.800 (s.e.= 0.044), which is a bit larger than the coefficient for 1989 found in Table 2 for the larger sample of households. We also note that the age coefficient is now -0.005 (s.e.=0.004) and that the college coefficient is 0.261 (s.e.=0.123).]

Columns (2) mimics column (1) for 1989. This column is different from Table 2 because the sample of households is n\ow smaller (1343 compared with the 2847 of Table 2). Despite the differences in samples, the coefficient on ln A is very similar [0.722 (s.e.=0.040)]. As mentioned above, this coefficient is substantially higher than the corresponding coefficient for 1983. Unlike the 1983 regression, age coefficient for 1989 is not significant. An interesting point is that the college variable is not significant for 1989, even though it was significant when we used the longer sample.

Column (3) uses the 1989 dependent variable with the 1989 ln A, age and college. The key to Column (3) is that it also includes ln A_{1983} (which we take as ln A_{t-1} in the theory of the previous section). The coefficient on the ln A_{1989} is 0.669 (s.e.=0.043). The lagged variable, ln A_{t-1}, has a positive and significant coefficient, 0.106 (s.e.=0.031). Columns (4) and (5) add ln(1-τ) to the estimates of columns (2) and (3) respectively. We note that the coefficients on ln(1-τ) are not significant and the rest of the coefficients change little.

To compute the implied coefficient on ln R, we need to know how ln A_{1989} relates to ln A_{1983}. The autoregression coefficient, displayed in Table 5, is 0.832 (s.e.=0.015). Using this coefficient to write ln A_{1983} as a function of ln A_{1983}, and plugging the result in the probit equation we see that the "overall" coefficient on ln A_{1989} would be 0.669+0.106/0.832 = 0.798.[27] This coefficient is a bit higher than but not very different from the one we get in Column (2) of Table 6 for the panel sample of households (which is 0.722 (s.e.=0.04).) The main lesson is, therefore, that extending the empirical analysis to a dynamic setup yields very similar results to the static framework.

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[27] I we use the coefficients of Column (5) instead, the implied coefficient is 0.672+0.107/0.83=0.801, which is still not too different from 0.722

X. Conclusions

This paper explores some of the behavioral distortions created by inflation. We start by pointing out that the distortion emphasized by inventory models of money demand - namely, the substitution of interest-bearing assets for monetary assets - is not relevant for a majority of households at current interest rates. The important decision is not the fraction of assets to be held in interest bearing form but whether to hold any amount of interest bearing assets at all. We call this decision the decision "*to adopt the financial technology*" or the "*extensive margin*" decision.

The theoretical and empirical implications of this realization are interesting and important. For example, the benefit of adopting the financial technology will typically be the amount of interest income that would otherwise have been foregone. This foregone interest is usually related to R (the nominal interest rate differential) times A (the amount of assets). Since the adoption decision will involve the comparison of the benefits of adoption with the costs, this highlights an interesting feature of our model: in the adoption decision, A and R matter in a multiplicative way. In other words, the benefits of adopting a technology are small if $R \cdot A$ are small, whether that is because the interest rate is small or the amount of assets are small. This result allows us to investigate the behavioral changes of money holders at low interest rates by looking at the behavior of people whose assets are very small. That is, we are able to explore the elasticity of money demand for interest rates close to zero, even though interest rates have not been close to zero in recent U.S. experience.

Another prediction of our setup is that the probability that a household owns positive amounts of interest bearing assets should be positively related to its financial wealth. All our empirical estimates confirm this prediction.

Our model also predicts that the interest elasticity of money demand is very small when the interest rates are low. Intuitively, the reason is that, when the nominal interest rate is close to zero, then the fraction of the population who decides to use interest bearing assets is negligible. Hence, even though the interest elasticity of the households who use such assets is big, their weight in the overall demand for money is so small that the aggregate effect is small. Any interest sensitivity resulting from marginal adoption is also small at low interest rates when the density of the adoption cost is small at very low costs. By making a normality assumption, we implicitly assume that the density does approach zero. However, Figure 6 shows that our micro data are consistent with this aspect of the normality assumption. Our prediction of low interest elasticity at low interest rates is crucial, for example, for the evaluation of the welfare costs of inflation. The consumer surplus approach applied by Bailey (1956), Lucas (1994) and others show that the welfare cost of inflation hinges fundamentally on the money demand elasticity at low interest rates. The conclusion of our model is, therefore, that the welfare cost of low inflation is low.

Our empirical estimates confirm the theoretical prediction that the interest elasticities of money demand are very low for low interest rates. For example, for economies whose per capita seigniorage is that is less than the United States in 1989 (per capita seigniorage is roughly the product of the nominal interest rate and money per household) the interest elasticity is 0.2. Interest elasticities are much higher for economies with higher intermediate levels of seigniorage. This suggests that a lowering of the U.S. nominal interest rate from 5% to 1% would have a much smaller welfare gain that lowering it from 9% to 5%.

We conclude this paper by highlighting some possible drawbacks of our methodology. First, the policy prescriptions should be qualified by the fact that we study only households. Inventory models may be more relevant for firms and firms' money demand elasticities may be large for a wide range of interest rates.[28] Foreigners also hold a fraction of the U.S. money supply so their behavioral change must also be considered. It may also be undesirable from either a positive or a normative point of view to use the consumer surplus approach to analyze the effects of policies on foreigners. Uncertainty may be associated with high rates of inflation, but we - like Bailey (1956), Lucas (1994), and others - have ignored this in our analysis. Our results therefore speak only to changes in the rate of inflation which do not change inflation related uncertainty.

[28]See Mulligan (1994) for some micro evidence on these points.

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Appendix

Likelihood Functions Used in the Paper

Model I: "Tobit" model, ignoring $\alpha = 1$ corner

Define Π_{0i} for each observation i that doesn't adopt and Π_{1i} for each observation that does adopt:

$$\ln \Pi_{0,i} \equiv \ln \Phi\left(- \frac{\ln A_i + \ln R_i - X_i \beta_1 + \ln[1 - L(A_i, R_i)] - \mu_\beta + \mu_v}{\sigma} \right)$$

$$\ln \Pi_{1,i} \equiv \ln \Phi\left(\frac{\ln A_i + \ln R_i - X_i \beta_1 + \ln[1 - L(A_i, R_i)] - \mu_\beta + \mu_v}{\sigma \sqrt{1 - \tilde{\rho}^2}} - \frac{\tilde{\rho}}{\sqrt{1 - \tilde{\rho}^2}} \frac{\ln \alpha_i - \ln[1 - L(A_i, R_i)] - \mu_v}{\sigma_v} \right)$$

$$+ \ln \phi\left(\frac{\ln \alpha_i - \ln[1 - L(A_i, R_i)] - \mu_v}{\sigma_v} \right) - \ln \sigma_v$$

$$\sigma \equiv \sqrt{\sigma_\beta^2 + \sigma_v^2 - \rho \sigma_\beta \sigma_v}$$

$$\tilde{\rho} \equiv \rho \frac{\sigma_\beta}{\sigma} - \frac{\sigma_v}{\sigma}$$

The log likelihood function is:

$$L(\mu_\beta, \sigma_\beta, \mu_v, \sigma_v, \beta_1, \rho) \equiv \sum_{i \mid i \text{ doesn't adopt}} \ln \Pi_{0i} + \sum_{i \mid i \text{ adopts}} \ln \Pi_{1i}$$

Model II: "Tobit" model, assuming $\rho = 0$

Define Π_{0i} for each observation i that doesn't adopt, Π_{1i} for each observation that adopts with $\alpha<1$, and Π_{1i} for each observation that adopts with $\alpha=1$:

$$\ln \Pi_{0,i} \equiv \ln \Phi\left(- \frac{\ln A_i + \ln R_i - X_i \beta_1 + \ln[1 - L(A_i, R_i)] - \mu_\beta + \mu_v}{\sigma} \right)$$

$$\ln \Pi_1 \equiv - \ln \sigma_v + \ln \Phi\left(\frac{\ln A_i + \ln R_i - X_i \beta_1 + \ln[1 - L(A_i, R_i)] - \mu_\beta + \mu_v}{\frac{\sigma}{\sigma_\beta} \sqrt{\sigma_\beta^2 - \sigma_v^2}} + \frac{\ln \alpha_i - \ln[1 - L(A_i, R_i)] - \mu_v}{\sqrt{\sigma_\beta^2 - \sigma_v^2}} \right)$$

$$+ \ln \phi\left(\frac{\ln \alpha_i - \ln[1 - L(A_i, R_i)] - \mu_v}{\sigma_v} \right)$$

$$\ln \Pi_{2,i} \equiv \ln \Phi\left(\frac{\ln A_i + \ln R_i - X_i \beta_1 - \mu_\beta}{\sigma_\beta} \right) + \ln \Phi\left(\frac{\ln[1 - L(A_i, R_i)] + \mu_v}{\sigma_v} \right)$$

$$\sigma \equiv \sqrt{\sigma_\beta^2 + \sigma_v^2 - \rho \sigma_\beta \sigma_v}$$

$$\tilde{\rho} \equiv \rho \frac{\sigma_\beta}{\sigma} - \frac{\sigma_v}{\sigma}$$

The log likelihood function is:

$$L(\mu_\beta, \sigma_\beta, \mu_v, \sigma_v, \beta_1, \rho) \equiv \sum_{i|i \text{ doesn't adopt}} \ln \Pi_{0i} + \sum_{i|i \text{ adopts}, \alpha<1} \ln \Pi_{1i} + \sum_{i|i \text{ adopts}, \alpha=1} \ln \Pi_{2i}$$

Model III: Probit model with instrumental variables.
Consider the model:

$$d_i = 1 \quad if\ \varepsilon_i \le \beta x_i$$
$$d_i = 0 \quad if\ \varepsilon_i > x_i \beta$$

$$x_i^* = x_i + \eta_i$$
$$x_i = z_i \gamma + \zeta_i$$

$$(\varepsilon, \eta, \zeta) \sim N(\mu, \Sigma)$$

where x_i is a scalar and z_i is a vector.
The log likelihood of observing $\{d_i, x_i^*, z_i\}$ is:

$$L(\mu_{\tilde{\varepsilon}}, \sigma_{\tilde{\varepsilon}}, \mu_{\zeta}, \sigma_{\zeta}, \beta, \gamma, \rho) =$$

$$-N \ln \sigma_\zeta - \frac{N}{2} \ln 2\pi - \frac{1}{2} \left(\frac{x_i^* - z_i \gamma - \mu_\zeta}{\sigma_\zeta} \right)^2$$

$$+ \sum_{i|d_i=1} \ln \Phi \left(\frac{\beta z_i \gamma - \mu_{\tilde{\varepsilon}}}{\sigma_{\tilde{\varepsilon}} \sqrt{1-\rho^2}} - \frac{\rho}{\sqrt{1-\rho^2}} \frac{x_i^* - z_i \gamma - \mu_\zeta}{\sigma_\zeta} \right)$$

$$+ \sum_{i|d_i=0} \ln \Phi \left(- \frac{\beta z_i \gamma - \mu_{\tilde{\varepsilon}}}{\sigma_{\tilde{\varepsilon}} \sqrt{1-\rho^2}} + \frac{\rho}{\sqrt{1-\rho^2}} \frac{x_i^* - z_i \gamma - \mu_\zeta}{\sigma_\zeta} \right)$$

$$\tilde{\varepsilon} \equiv \varepsilon - \beta\zeta , \quad \tilde{\zeta} \equiv \zeta + \eta , \quad \rho \equiv corr(\tilde{\varepsilon}, \tilde{\zeta})$$

This can obviously be generalized to allow the means to be a linear function a vector of variables as long as some of the z variables are excluded.

TABLE 1: PERCENT OF 1989 U. S. HOUSEHOLDS WITH INTEREST BEARING FINANCIAL ASSETS

	Have Interest Bearing Financial Assets?		
Have Checking Account?	No	Yes	Row Total
No	19%	7%	25%
Yes	40%	35%	75%
Column total	59%	42%	100%

Notes (1) A household is qualified as having a checking account if they have a nonzero balance in a checking account which they do not designate as a money market account.

(2) "Interest Bearing Financial Assets" are money market accounts, CDS, other bonds, mutual fund shares, and equities.

TABLE 2: STATIC MODEL WITH CONSTANT α
(PROBIT ESTIMATES)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln A	0.661 (0.023)	0.657 (0.024)	0.666 (0.025)	0.668 (0.026)	0.666 (0.025)	0.667 (0.026)	0.666 (0.026)
Age		-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.0007 (0.0031)
College		0.151 (0.077)	0.168 (0.079)	0.172 (0.080)	0.168 (0.079)	0.169 (0.079)	0.167 (0.079)
ln(1-τ)			0.471 (0.414)	0.350 (0.562)	0.472 (0.414)	0.466 (0.414)	0.561 (0.422)
ln Y				-0.018 (0.057)			
Distance					-0.0003 (0.0030)		
Poor Health						-0.010 (0.018)	
Retired							-0.116 (0.107)
constant	-5.637 (0.200)	-5.541 (0.208)	-5.466 (0.218)	-5.326 (0.490)	-5.464 (0.219)	-5.422 (0.232)	-5.519 (0.224)
N (#obs)	2842	2842	2842	2842	2842	2842	2842

Note: Dependent variable in all columns is: "1" if household has ANY amount of interest bearing assets and "0" otherwise. Standard Errors in Parenthesis.

TABLE 3: STATIC MODEL WITH CONSTANT α (IV-PROBIT ESTIMATES)

	(1)	(2)	(3)
ln A	0.35 (0.02)	0.722 (0.041)	0.58 (0.03)
ln (1-τ)	0.04 (0.30)	-0.028 (0.662)	-0.74 (0.52)
Age	--	-0.002 (0.004)	0.006 (0.003)
College	-0.14 (0.06)	0.100 (0.124)	0.037 (0.094)
Excluded instruments:	age polynomial	NO instruments	$\log(A_{1983})$, age polynomial
N (#obs)	2842	1342	1342

Note: Dependent variable in all columns is: "1" if household has ANY amount of interest bearing assets and "0" otherwise. Standard Errors in Parenthesis. The first column uses the full 1989 sample of households. The second and third columns use the panel sample of households that responded to both the 1983 and 1989 surveys.

TABLE 4: STATIC MODEL WITH ENDOGENOUS α
(TOBIT ESTIMATES)

	(1)	(2)	(3)	(4)
Adoption Equation				
ln A	0.66 (0.02)	0.67 (0.02)	0.59 (0.02)	0.53 (0.02)
ln (1-τ)		0.46 (0.41)	0.59 (0.02)	0.53 (0.02)
ln (1-L(A,R))	0	0	0.59 (0.02)	0.53 (0.02)
Age	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
College	0.15 (0.08)	0.16 (0.08)	0.20 (0.08)	0.20 (0.08)
Equation of Adopter's Money Demand				
ln A	-0.17 (0.05)	-0.24 (0.05)	-0.21 (0.05)	-0.21 (0.05)
ln (1-τ)		-1.55 (0.53)	-1.23 (0.45)	-0.99 (0.52)
ln Y				0.03 (0.03)
	unrestricted	unrestricted	restricted	restricted
N (#obs)	2847	2842	2842	2842

Note: Dependent variable in all columns is: "1" if household has ANY amount of interest bearing assets and "0" otherwise. Standard Errors in Parenthesis. The first 5 rows refer to the equation reflecting the adoption decision. The following three rows relate to the intensive margin decision.

TABLE 5A: PERCENTAGE OF HOUSEHOLDS WITH INTEREST BEARING ASSETS IN 1983 AND 1989

Have Interest Bearing Assets in 1983?	Have Interest Bearing Assets in 1989? Yes	No	Row Total
Yes	745 (50.4%)	115 (7.8%)	860 (58.2 %)
No	142 (9.6 %)	477 (32.2%)	619 (41.8 %)
Column total	887 (60 %)	592 (40 %)	1479 (100%)

TABLE 5B: AUTOREGRESSION OF ASSETS AND INCOME (1983-1989)

	constant	$\ln(A_{1983})$	$\ln(Y_{1983})$	R^2
$\ln(A_{1989})$	2.076 (0.153)	0.832 (0.015)		0.69
$\ln(Y_{1989})$	2.405 (0.216)		0.825 (0.021)	0.58

TABLE 6: DYNAMIC MODEL
(PROBIT ESTIMATES)

	1983 (1)	1989 (2)	1989 (3)	1989 (4)	1989 (5)
$\log(A_{1983})$	0.800 (0.044)		0.106 (0.031)		0.107 (0.032)
Age_{1983}	-0.005 (0.004)				
$College_{1983}$	0.261 (0.123)				
$\log(A_{1989})$		0.722 (0.040)	0.669 (0.043)	0.722 (0.041)	0.672 (0.044)
Age_{1989}		-0.002 (0.004)	-0.005 (0.004)	-0.002 (0.004)	-0.006 (0.004)
$College_{1989}$		0.103 (0.121)	0.033 (0.123)	0.100 (0.124)	0.042 (0.127)
$\ln(1-\tau)$				-0.027 (0.662)	0.271 (0.673)
Constant	-6.553 (0.375)	-6.214 (0.358)	-6.456 (0.375)	-6.214 (0.394)	-6.385 (0.405)
N	1343	1343	1343	1343	1343

Note: Dependent variable in all columns is: "1" if household has ANY amount of interest bearing assets and "0" otherwise. For column (1), the dependent variable applies to 1983. For columns (2) through (5), it applies to 1989. Standard Errors in Parenthesis.