ESSAYS IN EMPIRICAL ECONOMICS: BANK ACCESS AND NEW TECHNOLOGY ADOPTION AND STATES' MANAGEMENT OF UNEMPLOYMENT INSURANCE FINANCE

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Satadru Mukherjee

May 2012

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Satadru Mukherjee

APPROVED:

Aimee Chin, Ph.D.
Committee Chair

Bent Sorensen, Ph.D.

Elaine Liu, Ph.D.

Nishith Prakash, Ph.D.
University of Connecticut

John W. Roberts, Ph.D.
Dean, College of Liberal Arts and Social Sciences
Department of English

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Abstract

This dissertation is composed of three essays. The first essay examines the effect of bank branch expansion on High Yielding Variety (HYV) seed adoption by Indian households using the Additional Rural Incomes Survey (ARIS) and Rural Economic and Demographic Survey (REDS) Indian household panel data, and bank branch data from the Reserve Bank of India. I use the Indian government's social banking policy to provide exogenous variation in district bank access. This policy, in effect 1977 to 1990, forced banks to open more branches in financially less developed areas. I find that districts with lower initial financial development experienced significantly more branch openings during the social banking period (1977-1990). Moreover, I find that households in financially less developed districts were more likely to adopt HYV seeds during the social banking period consistent with the view that access to credit is a major determinant of new technology adoption.

In the second essay, following the empirical strategy developed in the first essay, I examine the effect of bank branch expansion on High Yielding Variety (HYV) seed adoption by Indian districts. I use the Indian government's social banking policy to provide exogenous variation in district bank access. This policy, in effect 1977 to 1990, forced banks to open more branches in financially less developed areas. Using data on district HYV use from the Evenson and McKinsey India Agriculture and Climate dataset, and bank branch data from the Reserve bank of India, I find that financially less developed districts increased HYV seed adoption during the social banking period, consistent with the view that access to credit is a major determinant of new technology adoption.

In the third essay (co-authored with Steven Craig, Wided Hemissi and Bent Sorensen), we study how state governments manage the finances of their Unemployment Insurance (UI) programs. The operation of the UI programs is separate from states' general budgets with clearly specified rules of saving (in a trust fund operated by the treasury) and spending, although spending includes a large discretionary component. Using a panel of US states we find that UI program spending and taxes are not described well by the PIH or by the Barro tax smoothing model. Instead, we find that states increase spending when their trust fund balance is high, and that trust fund balances seem to be clearly mean reverting. This pattern suggests that the data may be explained by a buffer stock model with forward looking but impatient politicians as suggested by Carroll (1997) for consumers. We split UI benefits spending into a compulsory part (explained by unemployment) and a discretionary part. Considering taxes as income and discretionary benefits as consumption, we calibrate and simulate a version of Carroll's buffer stock model. We find that the simulation results of the buffer stock model match well our data, where politicians adjust policy to stay close to the target level of savings as shown by simulation matching the covariance condition where consumption and savings move with differences from the target level of savings.

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Chapter 1

Access to Formal Banks and New Technology Adoption: Evidence from Indian Household Panel Data

1.1 Introduction

Technological innovation fosters economic development and is key towards sustaining high living standards around the world. Hence, delays in new technology adoption are puzzling in an environment where people know new technologies to be better than existing technologies. Comin and Hobijn (2010), in a recent study on technology diffusion between countries, show that cross-country variation in technology adoption explains at least 25 percent of income differences between countries. Hence it is important to analyze what causes these delays in technology adoption.

Economists identify credit constraints (Croppenstedt et al. 2003; Sunding and Zilberman, 2001; Barret et al., 2003), lack of education (Aldana et al., 2009; Foster and Rosenzweig, 1996; Huffman, 2001), and risk aversion (Liu, 2010; Engle-Warnick et al., 2006) as some potential barriers to new technology adoption. Delays in technology adoption are likely to be longer in developing countries, due to lower levels of human capital and less developed financial markets in these countries. It is widely recognized in the literature that lack of formal credit in the developing countries can prevent households from undertaking profitable investment projects, including investments in physical capital and human capital. Karlan and Morduch (2010) estimate the number of “unbanked” and “underbanked” adults worldwide to be around 2-3 billion, with the majority of these residing in the developing countries. In theory, improving access to formal credit can raise new technology adoption rates by removing credit constraints or lowering the cost of capital; however, to the extent that other barriers dominate, there may be no effect of improving access at least as far as new technology adoption is concerned. Though credit constraints have been proposed as a reason for delay in new technology adoption (e.g., Feder and O'Mara 1981), and the effect of credit access on agricultural investments have been analyzed (e.g., Binswanger, Khandker and Rosenzweig 1993), to my knowledge there has not been rigorous empirical investigation of whether improving access to formal credit affects new technology adoption.[1] This study attempts to fill the gap.

Specifically, I study the effect of formal bank access on High Yielding Variety (HYV) seed adoption in India. Researchers use agricultural technologies as a backdrop to study the broader questions of technology adoption decisions in developing countries. This is because a majority of the population derives income from agriculture and allied activities in these

[1] Binswanger, Khandker and Rosenzweig (1993) analyze the role of access to credit on agricultural investments but do not examine technology adoption decisions.

countries. Spread of new technologies in agriculture seems to be a natural way to ensure sustainable improvement in income for the millions of rural households in these countries.

It is difficult to identify a causal effect of bank access on HYV adoption. This is because regions with better bank access differ in many observed and unobserved ways from regions with worse bank access, including some factors that could affect HYV adoption. Therefore, correlations between bank access and HYV use are unlikely to have a causal interpretation. I exploit district-time variation in bank access generated by policy shifts in India regarding bank branching to identify the causal effect of bank access in HYV adoption. My difference-in-differences strategy is based on the one used by Burgess and Pande (2005) to identify the effect of bank access on poverty in India. Before 1977 and after 1990, banks were largely unconstrained in where they opened new branches. During 1977-1990, the Central Bank of India—with the goal of increasing equity in access to banks in India—required banks to open four branches in unbanked locations for each one branch opened elsewhere. This "social banking policy" dramatically increased the number of bank branches in initially less financially developed areas. Households in initially less financially developed areas during 1977-1990 were exposed to increased bank access due to the social banking policy. Using household panel data from the Additional Rural Incomes Survey (ARIS) and Rural Economic and Demographic Survey (REDS) and bank branch data from the Reserve Bank of India, I implement my difference-in-differences strategy with household fixed effects added. I find that households were more likely to adopt the new seed varieties when they had more access to formal credit. The significant impact of improved bank access on HYV adoption, though, appears limited to households that are the wealthiest or the most educated.

This paper is organized as follows. In the next section, I provide some background on HYV technology and discuss the related literature. I detail my empirical strategy in Section

1.3. After describing my data in Section 1.4, I present my results in Section 1.5. Section 1.6 concludes.

1.2 Background

1.2.1 HYV Seed Adoption in Developing Countries

HYV seeds were introduced in a number of developing countries including India in the mid-1960's to improve agricultural productivity and attain self-sufficiency in food grain production. Initial wheat and rice varieties released from the International Maize and Wheat Improvement Center (CIMMYT) in Mexico and the International Rice Research Institute (IRRI) in Philippines found widespread adoption in different countries due to their adaptability to diverse growing conditions. The HYV seeds spread faster in more favorable production environments with good irrigation systems, better infrastructure, and these areas experienced a tremendous increase in agricultural output immediately after initial adoption of the new varieties.

This phenomenal increase in agricultural production due to HYV seed adoption was characterized as a "Green Revolution." Following the initial success of HYV seed adoption, more countries switched to HYV seed cultivation over time. Evenson and Gollin (2003) find that the HYV seeds accounted for 21 percent of the growth in yields for all developing countries between 1961-1980, which they characterize as an "early Green Revolution" period. The impact was even higher during 1981-2000, a "late Green Revolution" period where HYV seeds contributed to almost 50 percent of the growth in yields for all developing countries. This shows that the adoption of HYV seeds had a substantial impact on world agricultural productivity over time.

The HYV seeds, generally semi-dwarf in stature (i.e. shorter than normal height), were less prone to lodging (falling down) at high levels of fertilizer application, besides having a higher grain to straw ratio that enabled them to produce more grain relative to traditional varieties. Also, shorter growing seasons of the HYV seeds allowed farmers to practice multiple cropping and thereby increase output. Despite these potential advantages of using HYV seeds, farmers willing to adopt HYV seeds needed to make upfront capital investment in irrigation if they had no stable access to water. Moreover, the working capital requirements of HYV seeds were higher than traditional seeds due to more intensive use of fertilizers and pesticides. The sensitivity of HYV seed yields to irrigation and fertilizer use implied that farmers living in cultivating areas with assured water supply and access to the complementary inputs for HYV seed cultivation were likely to be the initial adopters of HYV seeds.

Figure 1.1 (using data from Evenson 2005) shows the spread of rice HYV seeds in developing countries worldwide over time.[2] Overall differences in the share of total cultivable land devoted to rice HYV seeds between countries in Asia and those in Latin America, Africa and the Middle East reflect environmental differences in growing conditions of rice HYV's in these countries, i.e. it shows that countries in Asia were better suited to rice HYV cultivation than others. However the gradual diffusion of the modern seed varieties over time, as shown in Figure 1.1, suggests that even within countries where HYV seeds spread rapidly at the initial stages of adoption, there exists regional variation in the extent to which HYV seeds were adopted. Some regions might have adopted HYV seeds faster than others due to more favorable agro-climatic conditions, however even within these regions there was variation in household adoption of HYV and only gradually did adoption rates

[2]Data on the percentage of cultivable area devoted to HYV seeds is also available for other crops (for e.g. wheat, maize). However, rice is one of the most commonly grown crops, focusing on a single crop allows us to ignore differences in crop composition across regions that might affect HYV adoption.

rise. Hence it is a question why the HYV seed technology did not spread faster.

Zhang et al. (2002), using district panel data from India covering 280 districts for 25 years, show that the overall share of cropped area planted under HYV seeds increased from 17 percent in 1970 to 44 percent in 1985 and to 59 percent in 1995. They show that there exists substantial regional variation in HYV adoption rates between Indian states. These differences in adoption rates can be partly attributed to varying agro-ecological conditions and differences in rural infrastructure. The observation that differences in rural infrastructure affect HYV adoption suggest a possible role for bank access in HYV adoption, as investments in infrastructure may have greater complementarity in production with HYV seeds than traditional varieties.

Recognizing the role of local growing conditions in influencing adoption, Foster and Rosenzweig (1995), study the role of social learning in HYV seed adoption in India. They find that learning from neighbors' experiences increased HYV seed adoption in India. Additionally, Munshi (2003) finds that wheat cultivators in India relied more on social learning to adopt HYV seeds, because wheat HYV seeds were more robust to different growing conditions across the country. Rice HYV seeds, on the other hand, were more sensitive to unobserved input and soil characteristics than the wheat varieties. Therefore, rice cultivators depended more on own experimentation to adopt the new seed varieties.

Feder and O'Mara (1981) recognize that credit constraints were likely to limit HYV seed adoption due to higher working capital requirements of using HYV seeds. Unavailability of cash to buy HYV seeds, fertilizers and pesticides would restrict farmers from adopting HYV seeds. Though researchers suggest credit constraints as a major limiting factor to new technology adoption, no one has rigorously quantified the role of access to banks on new technology adoption. This paper contributes by assessing the role of formal credit access on HYV technology adoption in India.

In the period after independence in 1947, rural financial markets in India were dominated by informal lending institutions. The All-India Credit Survey Report published by the Indian Central Bank in 1954 finds that moneylenders accounted for close to 70 percent of the rural lending in 1951. Banks were mostly confined to finance trade and commerce activities in urban areas during that period. Burgess and Pande (2003) discuss some of the findings of this report. In response to the prevailing conditions in the rural financial markets, the Government of India pursued a development strategy that sought to improve rural bank access over time. As a first step, all banks with nationwide deposits greater than 500 million Rupees were nationalized by the government in 1969. Banerjee, Cole and Duflo (2004) point out that nationalization resulted in bringing the total number of branches under government control to 84 percent.

After bank nationalization in 1969, the government launched a branch expansion program to increase bank access in rural areas. As a part of the program, the government adopted a social banking policy between 1977-1990 that led to a tremendous growth in branch openings in unbanked locations during that period. The policy rule was absent outside this period (I discuss this in greater detail in Section 1.3.2). Burgess and Pande (2005) show that the number of branches opened in unbanked locations in 16 major states increased from 105 to 29,109 between 1961 and 2000, with 80 percent of this expansion taking place between 1977 and 1990. I exploit these policy shifts to identify the causal effect of formal credit access on HYV seed adoption.

1.2.2 Related Literature

This study is related to two bodies of literature. The first is the extensive literature on the determinants of new technology adoption. Feder, Just and Zilberman (1985) and Sunding and Zilberman (2001) summarize the main factors influencing agricultural innovation in developing countries. Foster and Rosenzweig (1996), using the same household panel data from India as I do below, show that educated farmers were more likely to adopt HYV seeds since they were better capable of using new information about HYV seeds than uneducated farmers. Ali (2011), in a study of HYV seed adoption in Bangladesh, shows that rural road improvement enabled people to devote more acreage to HYV rice cultivation. This highlights the role of better infrastructure in HYV seed adoption decisions.

More recent studies based on field experiments in developing countries highlight how certain behavioral characteristics of individuals can influence new technology adoption decisions. Duflo, Kremer and Robinson (2011) find that procrastination led to low fertilizer use by maize cultivators in Kenya, despite high annualized returns to yield from fertilizer use. They show how small time limited discounts in fertilizers at the time of harvest enabled farmers to commit themselves to fertilizer purchase, which led to a substantial increase in fertilizer use. Liu (2010) shows in an experimental study about Bt cotton adopters in China that farmer's perceived risks about the effectiveness of Bt cotton led to delays in adoption of the new variety. This happened despite scientific evidence showing that Bt cotton was more pest resistant, and not riskier than traditional varieties of cotton.

The second body of literature to which this paper is related is the recent literature on the effects of expanding formal credit market access.[3] To identify causal relationships, these studies use variation in credit access generated by randomized experiments and natural

[3]Karlan and Morduch (2010) provide a nice summary of access to finance in developing countries.

experiments.

De Mel, McKenzie and Woodruff (2008), use randomized grants to generate shocks to capital stock for a set of Sri Lankan enterprises, and find the average real returns to be 4.6 percent to 5.3 percent per month. Banerjee et al. (2010) find from a randomized experiment in India that households who are randomly assigned to have better access to microfinance institutions are more likely to invest in business assets. Karlan and Zinman (2008), in an experimental study in South Africa, measure price elasticities of demand for microcredit. They mail out credit offers to 50,000 former clients of a microfinance institution with randomly assigned interest rates, and find that borrowers are less sensitive to price changes than expected, suggesting a high unmet demand for credit.

Two recent studies exploit natural experiments, in particular, policy shifts, to identify the effects of better bank access. Banerjee and Duflo (2008), in a study of medium-sized firms in India, find that policy-induced change in eligibility rules for receiving targeted credit led to increase in bank lending and revenues for newly eligible firms compared to the firms that were already eligible for receiving targeted credit. Burgess and Pande (2005) find that policy-driven rural bank branch expansion in India was able to explain a 14 percentage decline in rural poverty during 1961-2000. In this study, I will adopt the identification strategy used in Burgess and Pande (2005) to study the role of bank access in technology adoption.

1.3 Empirical Strategy

1.3.1 Conceptual Framework

To fix ideas, in this subsection I discuss a simple framework in which increased bank access might impact technology adoption. A firm (here, a farming household) is deciding at the beginning of the period whether to use the traditional technology or a new technology (here, HYV technology) to produce its output. In general, a profit-maximizing firm will choose the technology that maximizes its expected profits, so a firm will choose the new technology if it has higher expected profits than the traditional technology.[4]

Credit market imperfections, however, may cause a household to use the traditional technology even when the HYV technology offers higher expected profits. HYV technology offers higher expected yield and enables higher cropping intensity-which increases output and therefore revenues for the firm, at least in expectation-but also involves more cash outlay for inputs. Most notably, relative to traditional seeds, HYV seeds need steady water access (achievable via irrigation investments) and intensive use of fertilizer. If not coupled with irrigation and more fertilizer, the HYV seeds will not provide higher expected profit than traditional seeds. Thus, if a household cannot pay for irrigation and additional fertilizer, then it is better off choosing the traditional technology even if this household's expected profit from using HYV technology (HYV seeds and the requisite other inputs) is higher than that from using traditional technology. Given the higher cash outlays required to implement HYV technology, it becomes apparent how credit market imperfections can impede new technology adoption. One story involves households that are credit constrained

[4] In the case where the firm is a family enterprise, the objective function might be to maximize expected utility rather than expected profit (i.e., the firm may not be risk neutral, and its risk preferences enter the production decision). However, note that even for risk averse households, HYV adoption (which is perceived as riskier) is increasing in its expected profitability; however, instead of adopting the new technology when the difference in expected profits between the new and traditional technologies is greater than zero, the household adopts it when this difference is greater than the certainty equivalent.

having a limited ability to borrow. These are households that would adopt HYV technology if they could afford to pay for the initial costs of adoption, but because they cannot (and are unable to get a loan), they are forced to stay with the traditional technology. Bank branch expansion relaxes the household resource constraint, increasing household's ability to get a loan (which is expected to be repaid easily with profits realized at the end of the period), and thereby raises HYV adoption.

Even among households who are not credit constrained, credit market imperfections can reduce HYV adoption. In developing countries, often households have some access to informal credit such as from local moneylenders, relatives and friends. Local moneylenders generally charge very high interest rates, which are much greater than the area's bank lending rates (which in turn are higher than interest paid on deposits). There could exist households that have an unlimited ability to borrow—and as such, are not credit constrained—but their marginal cost of capital may be sufficiently high that the expected profit of using HYV technology (which requires borrowing to implement) may be less than that of using the traditional technology. Bank branch expansion tends to lower the cost of capital to households (e.g., banks charge lower interest rates than moneylenders, or with more branches there is more competition in lending which could lower interest rates for all sources of lending). A lower cost of capital increases the expected profit of using the HYV technology, thereby raising the likelihood of HYV adoption.

To summarize, through relaxing credit constraints and lowering the cost of capital, increasing bank access can be expected to raise HYV adoption. However, it is possible that reasons other than nonexistent or expensive credit are the limiting factors for why a household does not adopt HYV. In such a case, we would not see a relationship between bank access and HYV adoption. Thus, it is an empirical question whether poorly developed credit markets in India impeded the spread of HYV technology.

1.3.2 Identification Strategy

Identifying the causal effect of bank access on HYV seed adoption is difficult because bank access can be potentially endogenous. Banks do not choose where to locate on a random basis, and instead the location decision depends on many observable and unobservable factors, such as the location's population density, productivity and unmet demand for credit. Some of these factors might be correlated with HYV seed adoption, such that simple regressions of HYV adoption on bank access will in general not provide the causal effect of bank access on HYV adoption. To address the endogeneity problem, I exploit district-time variation in the new bank branch openings induced by shifts in India's policies regarding bank branching.

In 1969, the 14 largest commercial banks of India were nationalized. After nationalization, the Indian government embarked on a bank branch expansion program that intended to equalize bank access across Indian states. The Indian Central Bank, which is called the Reserve Bank of India, made a list of unbanked locations meeting a certain population cutoff that were to be targeted for new branch openings. As the same population cutoff was applied across India, regions with a lower initial stock of bank branches per capita were likely to be the primary targets of new branch openings. This bank expansion program was not effective in improving equity in bank access–banks apparently did not have much incentive to open new branches in less financially developed areas–thus in 1977 the Reserve Bank of India shifted to a more aggressive policy. The new branch licensing policy required banks to open 4 branches in unbanked locations in order to open one branch in an already banked location (this is sometimes called the 1:4 branch licensing policy; following Burgess and Pande (2005), I will also refer to it as the social banking policy). Further, to ensure that the banks served the locations where they opened new branches (rather than operating phantom branches with no real lending activity), the Reserve Bank of India required branches to maintain a credit-deposit ratio of 60 percent within their geographical area of operation. The social banking policy was discontinued in 1990. However, banks were not allowed to close if a branch was the only one serving a particular location, and thus banks that were bound by the social banking policy to open branches in less financially developed areas typically had to maintain those branches even after the discontinuation of social banking. But after 1990, banks were once again free to locate new branches where they wished, as they had been able to do prior to 1977.

Burgess and Pande (2005) use the adoption and discontinuation of the social banking policy to identify the causal effect of bank access on rural poverty in India. They use state panel data and take advantage of the fact that the social banking policy increased bank access more for states that were initially less financially developed than states that were more financially developed. I apply their identification strategy to a different outcome—HYV technology adoption—and use district-time rather than state-time variation in exposure to social banking. This is a difference-in-differences identification strategy—essentially, I take the change over time in HYV adoption among districts with lower initial financial development, then I subtract out the change over time in HYV adoption among districts with higher initial financial development—to remove the secular change over time and recover the causal effect of social banking. The following equation describes this:

$$UseHYV_{idt} = \alpha_v + \beta_t + \gamma(B_{d1961} * SocialBankingPeriod_t) + \pi * X_{idt} + e_{idt} \tag{1.1}$$

where $UseHYV_{idt}$ is a dummy variable indicating whether household i in district d uses

HYV seeds at time t. B_{d1961} is initial financial development of a district (measured as the number of bank branches per capita in a district in 1961). The Social Banking Period is a dummy variable indicating if the year falls between 1977-1990. X_{idt} are household, district or state characteristics. α_v are village fixed effects (below, I will also use household fixed effects) and β_t are year fixed effects.

The parameter of interest is γ, the difference-in-differences in HYV adoption. Under the parallel trend assumption–i.e., without social banking, the change over time in HYV adoption in less financially developed areas would have been the same as the change in more financially developed areas–this gives the causal effect of social banking. (As a technical matter, it gives the *negative* of the effect of social banking because it is the less financially developed areas that receive more new bank branches under social banking). It is plausible that less financially developed areas are less developed in other respects as well, so we might be concerned that they might have been slower to adopt new technologies (or, faster, in the case of mean reversion). To mitigate this concern, I always control for year-specific effects of initial state income, population density and rural share on HYV seed adoption. In a robustness check below, I will also control for agricultural development programs in the village; to the extent that the placement of these programs is correlated with initial financial development, then γ could be capturing the effects of these programs on HYV adoption in addition to the effects of social banking (this turns out not to be the case).

1.4 Data

The primary data source for my empirical analysis is the Additional Rural Incomes Survey (ARIS) and Rural Economic and Demographic Survey (REDS) data collected by the National Council of Applied Economic Research (NCAER) in India. The ARIS/REDS was first conducted in 1968-69 followed by 1969-1970, 1970-71; households in the 1971 survey were followed up in 1982 and 1999. The survey is longitudinal, and designed to be nationally representative of the rural population. The timing of the rounds of ARIS/REDS makes it a good dataset with which to implement my empirical strategy because there are observations from before (1971), during (1982) and after (1999) the social banking period of 1977-1990. Additionally, the panel structure enables me to address issues of unobserved household heterogeneity (my preferred estimates use household fixed effects). Moreover, it has rich data on the household, and, most importantly for my purpose, has information on household HYV adoption in each round. The measure of HYV use that I use in this paper is a binary variable indicating whether a household used HYV seeds. This measure captures the extensive margin of technology adoption, i.e., the margin of using the new technology at all, or not using at all. Foster and Rosenzweig (1995) also use the ARIS/REDS data to study HYV adoption, and more information about these data are provided there as well as from NCAER.

My sample comprises 1404 households living in 223 villages, across 92 districts, in 14 major states in India. This is about 30 percent of the total households that completed surveys in 1971 (4527 households in 259 villages), and results from the following sample restrictions. First, I restrict to households that primarily cultivate their own plots of land in the baseline year 1971; these are the households who are making production decisions, with HYV decision being one of these decisions. Non-cultivators in 1971 are excluded from the sample since these households do not make a decision whether to adopt HYV seeds or not.[5] Second, I restrict to households that completed surveys in all three years; by using

[5]Many of these non-cultivators are agricultural laborers working on other people's farms. From the original 4527 households in 1971, 1289 are non-cultivators, leaving me with 3238 cultivating households. Of the 3238 cultivating households, I drop 176 households in Assam and Jammu and Kashmir from my sample since households in these states are not surveyed in all three years. Next, I drop 48 households in Himachal Pradesh from my sample since I do not have data on initial state characteristics for Himachal Pradesh.

a balanced panel, I avoid concerns that the estimated effects are confounded by changes in sample composition over time.[6] In a robustness check detailed in subsection 1.5.2, I analyze whether the estimated effect of the social banking policy on household HYV adoption is driven by restricting the sample to a balanced panel of households across the three years. First, I re-estimate the effect of bank access on HYV adoption using an unbalanced panel data on households and find that the results are similar. Second, I check if sample attrition over time is affected by the social banking policy and I find that sample attrition over time is not caused by the social banking policy. These two findings suggest that the results presented below are not driven by my decision to focus analysis on the three-year balanced panel. (I discuss this in more detail in subsection 1.5.2).

For measuring bank access in districts, I use bank branch data from the Reserve Bank of India. Based on the location and year opened information for each bank branch, I aggregate to a district-year data set on cumulative number of branches opened over the period 1961-2000. Based on this and district-wise population counts from Census of India 1961, I form two variables for all districts covered by the ARIS/REDS sample. The first is the number of bank branches in each year per 10,000 persons in 1961, and captures the prevalence of banks in a district in a given year. The second is the number of bank branches in 1961 per 10,000 persons in 1961, and captures the district's initial financial development. In the paper I refer to bank branches per 10,000 persons as bank branches per capita.[7]

In order to form the measures of initial financial development and number bank branches per capita, and in order to merge these bank branch variables into the ARIS/REDS sample, I

Lastly, I drop 5 households from a district in Haryana with no data on the 1961 population. This leaves me with 3009 cultivating households in 1971.

[6] Of the 3009 cultivating households, 1077 leave the sample beginning in 1982 and 528 leave the sample beginning in 1999, leaving me with 1404 households.

[7] Burgess and Pande (2005) use number of bank branches in 1961 per 10,000 persons in the state for their measure of initial financial development, and I apply their definition to the district level.

had to contend with the fact that many districts in India underwent major boundary changes between 1961 and 2000. While 65 out of the 93 ARIS/REDS districts in the bank branch dataset have either remained unchanged, or split into smaller districts with no overall change in area, the rest of the districts have undergone more complex boundary changes. Since I use the 1961 census population to construct the measure of initial financial development, as well as the cumulative number of bank branches per capita, I persist with the 1961 district definitions to form a consistent measure of both the variables. I use information from the India Administrative Atlas tables, published by the Census of India, and from Kumar and Somanathan (2009) to code the district boundary changes for the districts appearing in my ARIS/REDS sample. For the districts that had complex boundary changes, I use population apportionment to form a measure of initial financial development that is consistent with the 1961 district definitions. I use the same method to construct the cumulative number of bank branches per capita in a district in a given year.

Besides household HYV use and demographic variables from the ARIS/REDS and bank branch variables from the Reserve Bank of India, I also use several state-level variables in my analysis to control for some potential differential trends: state income, population density, and number of rural locations, all measured in 1961. I obtain these variables from Burgess and Pande (2005). The original data source for state income is the Department of Statistics, Ministry of Planning, Government of India, and for population density and number of rural locations is the 1961 Census of India. Table 1.1 displays the means and standard deviations of the variables used in the empirical analysis below. Panel A shows the descriptive statistics for the district panel data on bank branches for 1961-2000 covering all the districts represented in the ARIS/REDS sample, which I use in subsection 1.5.1 to document the impact of the social banking policy on the number of bank branches. Panel

B shows the descriptive statistics for the household panel data, which I use to analyze the impact of social banking on HYV adoption (in subsection 1.5.2).

1.5 Results

1.5.1 Effect of Social Banking Policy on Bank Access

In this subsection, I evaluate whether the social banking policy increased the number of bank branches in financially less developed districts. I estimate the year-wise effect of initial financial development on branch openings using district panel data. I restrict the sample to districts covered by the ARIS/REDS household survey; the motivation here is to provide evidence for interpreting the reduced-form effects of social banking policy on household adoption of HYV technology that I estimate in the next subsection as related to improved bank access. The specific equation I estimate is:

$$B_{dt} = \alpha_d + \beta_t + \gamma_t * B_{d1961} + \delta_t * X_{s1961} + e_{dt} \tag{1.2}$$

where B_{dt} is the cumulative number of bank branches per capita in a district d in year t, and B_{d1961} is a measure of initial financial development of a district (specifically, it is the total number of bank branches per capita in a district d in 1961). α_d are district fixed effects, controlling for all time-invariant district characteristics that might affect the outcome. β_t are year fixed effects, controlling for aggregate time effects common to all districts. X_{s1961} are state initial conditions, log state real per capita income, log population density and log number of rural locations per capita (which is a measure of rural share in a state), all measured in 1961. These variables are time invariant variables at the state level, and as such are subsumed by the district fixed effects. I use them to control for some potential differential trends between more and less financially developed areas; δ_t captures the year-specific effects of the state initial conditions on the cumulative number of bank branches per capita in a district. The parameters of interest are γ_t, which are the year-specific effects of initial financial development on the cumulative number of bank branches per capita in a district relative to 1961 for a one-unit increase in initial financial development.

I estimate Equation 1.2 using ordinary least squares (OLS) and graph the γ_t in Figure 1.2A (note the omitted year is 1961, so the interpretation of γ_t is the change in number of branches relative to 1961 for a one-unit increase in initial financial development). Figure 1.2A shows that new branch openings in a district was positively related to the district's initial financial development until 1977 (as indicated by the positive slope; new branch openings equal this year's stock of branches less the previous year's). Beginning in 1977, though, the relationship between new branch openings and initial financial development turned negative. This was the year when the social banking policy began, requiring banks to open four branches in unbanked areas for each bank they opened in banked areas. The social banking policy was in effect between 1977-1990, and Figure 1.2A shows that it was exactly during these years that new branch openings were inversely related to initial financial development. After 1990, when the social banking policy was discontinued, the relationship between new branch openings and initial financial development returned to positive, as it had been prior to the social banking period. These patterns suggest that the social banking policy caused rapid branch growth in the financially less developed districts between 1977-1990. Note in Equation 1.2, that I already control for some differential trends along dimensions that are correlated with initial financial development; in particular, I have controlled for year-specific effects of state initial income, density and urbanicity. Nevertheless, there could still be a concern that the trend reversal beginning in 1977 may just reflect mean reversion, in which financially less developed areas catch up with more developed ones. However, the fact that after 1990, the trend reverses again (returning to a positive relationship between new branch openings initial financial development) suggests that the initial reversal in 1977 is not mean reversion (it would be extraordinarily coincidental for the mean reversion to occur exactly beginning in 1977 and ending in 1990).

I re-estimate Equation 1.2 by using the change in number of branches (i.e., B_{dt}-$B_{d,t-1}$ as my left hand side variable and graph these coefficients in Figure 1.2B. These coefficients show the year to year difference in coefficients displayed in Figure 1.2A, and as such focus on the slope of Figure 1.2A. These coefficients are the year-specific effects of initial financial development on the *change in* (as opposed to *cumulative* in Figure 1.2A) number of bank branches per capita in a district. Thus, Figure 1.2B directly shows how new branch openings were related to the district's initial financial development between 1962-2000.[8]

Following Burgess and Pande (2005), I summarize the trend reversals in the relationship between initial financial development and branch openings in a district by estimating a linear trend break model:

$$B_{dt} = \alpha_d + \beta_t + \gamma_1(B_{d1961} * [t - 1961]) + \gamma_2(B_{d1961} * [t - 1977]) \quad (1.3)$$

$$+\gamma_3(B_{d1961} * [t - 1990] + \gamma_4(B_{d1961} * P_{1977}) + \gamma_5(B_{d1961} * P_{1990}) + \delta_t * X_{s1961} + e_{dt}$$

where the linear time trends are given by [t-1961],[t-1977] and [t-1990]. These time trends switch on in 1961, 1977 and 1990 respectively. The time trends are interacted with the

[8] As the dependent variable is a first difference, the observations for 1961 drop because there is no 1960 data to use to compute the first difference. The interpretation of γ_t now is the change in new branch openings relative to the 1962-1961 change for a unit increase in initial financial development. As already seen by the slope of Figure 1.2A, new branch openings were positively related to the district's initial financial development until 1977. During the Social Banking period of 1977-1990, new branch openings were negatively related to the district's initial financial development. After 1990, new branch openings were positively related to the district's initial financial development, but this positive relationship is weaker than in the pre-1977 period.

measure of district's initial financial development B_{d1961}. P_{1977} and P_{1990} are year dummies that equal one from 1977 onwards and 1990 onwards, respectively. They are interacted with the measure of district's initial financial development B_{d1961}. The linear trend break model captures the average trend relationship between initial financial development and bank branch expansion during 1961-1977, and the corresponding changes in this trend relationship during 1977-1990 and 1990-2000.

Table 1.2 shows the results from estimating the linear trend break model (Equation 1.3) using OLS. Between 1961-1977, one additional point of initial financial development significantly increased the cumulative number of bank branches in a district by 0.16 branches per capita annually. On the other hand, between 1977-1990, one additional point of initial financial development significantly reduced the cumulative number of bank branches in a district by 0.02 branches per capita annually (the change in trend relative to the previous period is -0.18, leading to an overall trend in this period of 0.16-0.18=-0.02). After 1990, one additional point of initial financial development significantly increased the cumulative number of bank branches in a district by 0.10 branches per capita annually. These regressions confirm the patterns visually observed in Figures 1.2A and 1.2B, and further reveal that the trend changes in 1977 and 1990 are statistically significant at the 5 percent level. They provide convincing evidence that social banking policy caused rapid branch growth in financially less developed districts. It appears that banks left alone would not have expanded as much in financially less developed districts were it not for this policy, as immediately after the policy was discontinued, the banks reverted to opening new branches in better developed areas.

1.5.2 Effect of Social Banking Policy on HYV Technology Adoption

I proceed by estimating the effect of social banking policy on HYV technology adoption by farming households. I take advantage of the district-time variation in this policy—it was in effect between 1977-1990, and expanded bank access significantly more in initially less financially developed districts—to estimate its impact. Specifically, I use a difference-in-differences strategy in which I compare household HYV technology use before and after the social banking period, between households in less and more financially developed districts. I implement this strategy using balanced household panel data from the ARIS/REDS, which contains data for three years: 1971, 1982 and 1999. 1971 falls before the social banking period, 1982 is during it, and 1999 is after it. Thus, treatment to the social banking period is indicated by an interaction between initial financial development and a dummy for the year 1982, and its coefficient is the difference-in-differences estimate of the effect of the social banking policy. The full equation I estimate is:

$$\begin{aligned} UseHYV_{idt} = \alpha_v + \beta_t + \gamma_1(B_{d1961} * DUMMY1982_t) \\ +\gamma_2(B_{d1961} * DUMMY1999_t) + \kappa(AgeControls_{idt}) + \theta(EducationControls_{idt}) \\ +\rho(LandholdingControls_{idt}) + \delta_t * X_{s1961} + e_{idt} \end{aligned} \tag{1.4}$$

where $UseHYV_{idt}$ is a dummy variable equal to 1 if household i located in district d uses HYV seed in year t and 0 otherwise. α_v and β_t are village fixed effects and year fixed effects respectively. B_{d1961} is the measure of initial financial development of district d (specifically, it is the total number of bank branches per capita in a district d in 1961). $DUMMY1982_t$ and $DUMMY1999_t$ are year dummies which equal 1 if the year is equal to 1982 and 1999, respectively. $AgeControls_{idt}$ consists of age and age squared of the household head. The household head's educational attainment in 1971 is measured in three mutually exclusive categories: illiterate, primary schooling, and more than primary schooling. I include in $EducationControls_{idt}$ dummies for primary schooling and more than primary schooling, along with these variables' interactions with the 1982 year dummy (the omitted education category is illiterate). Based on the amount of land the household reports owning in 1971, I divide households into four quartiles of landholdings. I include in $LandownershipControls_{idt}$ dummies for the three higher quartiles, along with these variables' interactions with the 1982 year dummy (the omitted category is the bottom quartile). I also control for the year-specific effects of initial state conditions X_{s1961} on HYV seed adoption. The main coefficient of interest in Equation 1.4 is γ_1, which gives effect of the social banking policy. γ_2 provides the difference-in-differences in HYV use where the "after year" is 1999 and the "before year" is 1971. As the social banking policy is discontinued after 1990, the interaction term between initial financial development and the 1999 dummy no longer captures the effect of social banking policy.[9]

Table 1.3 shows the results of estimating Equation 1.4 using OLS. The policy variable is at the district-time level, however there could be serial correlation among observations within the same district, therefore I cluster the standard errors by district (Bertrand, Duflo and Mullainathan, 2002). In Column 1, I report results that exclude household controls (age, education and landholdings). I find a significant negative coefficient for the interaction between initial financial development and the 1982 year dummy (row 1). As documented in Section 1.5.1, the social banking policy expanded bank access in districts with lower initial financial development, thus this negative coefficient indicates that better bank access increases household HYV adoption (i.e., to get the effect of social banking, consider a

[9]Figures 1.2A and 1.2B in Section 1.5.1 make clear that new branch openings were no longer negatively correlated with initial financial development after 1990.

decrease in the initial financial development measure). In Column 2, I add the household controls and the estimated coefficient is basically unchanged. In Column 3, I control for household fixed effects—which controls for all time-invariant attributes of the household, whether they are observable or not—and again find a similar coefficient. However the standard error increases somewhat, as the degrees of freedom are materially reduced, and so this coefficient is significant only at the 10 percent level, compared to the 5 percent level in Columns 1 and 2.

Regarding the coefficients for the other variables in Equation 1.4, several things are worth noting. First, households with higher initial landholdings are significantly more likely to adopt HYV technology. This is consistent with Foster and Rosenzweig (1995). Second, household head's age and educational attainment do not significantly affect HYV adoption. This is different from Foster and Rosenzweig (1996); I explore this more below.

To summarize the Table 1.3 results, I find that households in financially less developed districts were more likely to adopt HYV seeds in 1982, that is during the social banking period. Thus bank access had a positive effect on HYV seed adoption. The standard deviation of initial financial development of the ARIS/REDS districts in the household sample is 0.08 branches per capita (see Table 1.1). Households located in a district that had one standard deviation lower initial financial development than another district were 9 percentage points (=-0.08*-1.18 coefficient from Column 3) more likely to adopt HYV seeds in 1982 (during the social banking period) relative to 1971 than the average district.

In Table 1.4, I explore heterogeneity in the effect of the social banking policy by landholdings and education. In Column 1, I re-report the result of Table 1.3, Column 3 for ease of comparison to remaining columns of the table. In Column 2, I add to the Column 1 specification interactions between the treatment variable and dummies for the top three quartiles of landownership; thus the coefficient for the treatment variable itself gives the effect for the lowest landownership quartile. I find that it is households in the top landownership quartile alone whose HYV adoption decisions significantly change due to social banking.[10] Social banking expanded access to credit to the poor as well as the rich (Burgess, Pande and Wong 2005), and moreover it might be expected that the lower landholding quartiles were more credit constrained, therefore it is somewhat surprising that social banking increases HYV adoption only for the top quartile. This is consistent with wealthier households getting a disproportionate share of the increase in credit brought about by social banking (poorer households may have received more credit too, but possibly the credit increase was still not enough to buy the inputs needed to use HYV); in Uttar Pradesh, Kochar (2011) finds that more bank access during the social banking period had a larger effect on the per capita expenditure of the nonpoor than on the poor. She finds supporting evidence suggesting that availability of banks increased loans to the nonpoor by more than it did for the poor. However, it is also consistent with some other factors besides fund availability being the limiting factors for a household's decision not to use HYV, and these factors may be more prevalent among households with less land relative to the top quartile of households.

In Column 3, I explore heterogeneity in effect of social banking by household head's educational attainment (I add to the Column 1 specification interactions between the treatment variable and dummies for educational attainment). I find that households where the head has more than primary education are significantly more likely to adopt HYV due to social banking. HYV use in households where the head has at most completed primary school does not appear responsive to social banking. Foster and Rosenzweig (1996) find that HYV

[10]The effect for the top quartile is -2.86 (which is the sum of the first row's coefficient of -0.94 and the fifth row's coefficient of -1.92) and this is significant at the 1 percent level; that the -1.92 is significant indicates that the effect of social banking significantly differs between the top and bottom landholding quartiles.

technology is complementary with skill, so it makes sense that the most educated households are the ones adopting HYV in response to social banking. However, recall that the main effects for education in Table 1.3 were insignificant. Why does education matter only when interacted with the social banking policy? It is possible that the households where the heads have at least primary schooling are knowledgeable enough to implement the HYV technology, however, they may face credit constraints, such that only when social banking improves bank access do they adopt.

Education and landholdings are positively correlated, so it is possible that the heterogeneity in effect of social banking by landholdings found in Column 2 and the heterogeneity by education found in Column 3 are reflecting the same thing. In Column 4, I allow for both types of heterogeneity and find that both neither the significant effect for the households in the top quartile of landownership, nor the significant effect for households with heads with more than primary education, disappear-they appear to be distinct phenomena. These point estimates indicate the following. First, households with above-primary-education heads located in a district that had one standard deviation lower initial financial development than another district were 16 percentage points (=-0.08 *(-0.60 -1.41) coefficient from Column 4, rows 1 and 7) more likely to adopt HYV seeds in 1982 (during the social banking period) relative to 1971 than the average district. Second, households in the top quartile of landownership located in a district that had one standard deviation lower initial financial development than another district were 19 percentage points (=-0.08 *(-0.60 -1.76) coefficient from Column 4, rows 1 and 5) more likely to adopt HYV seeds in 1982 (during the social banking period) relative to 1971 than the average district. Both these effects are significant at the 5 percent level.

As a robustness check, I control for two agricultural development programs: Intensive Agricultural Development Program (IADP)and Intensive Agricultural Area Program (IAAP). The IADP aimed at developing a package of improved agricultural practices and assisting farmers to develop farm production plans that maximized their net returns from cultivation; 278 households in my sample lived in villages covered by the IADP. 597 households lived in villages covered by the IAAP, which also aimed at improving agricultural practices but on a less intensive scale as IADP. The programs are likely correlated with agricultural outcomes such as HYV adoption, and to the extent that the placement of these programs is correlated with district financial development, then it is not longer possible to interpret the difference-in-differences estimates in Tables 1.3 and 1.4 as due to social banking as they could potentially reflect the effects of these agricultural development programs too. To address this concern I control for the year-wise effect of a village being covered by the IADP and IAAP. Table 1.5 reports these results. It can be seen that all the previous findings remain. Thus, contemporaneous agricultural development programs do not account for my findings.

As an additional robustness check, I test whether the effect of the social banking policy on household HYV adoption is driven by restricting the sample to a balanced panel of households. I explore the sensitivity of my results to my sample restrictions in two ways. First, I re-estimate the reduced form effects of bank access on HYV adoption using an unbalanced panel data on cultivating households and compare these results to those from using a balanced panel with data for all three survey years 1971, 1982 and 1999. Table 1.6 shows the results of this analysis. In Columns 1 and 2, I estimate equation 1.4 using a balanced panel of 1932 households for 1971 and 1982, I re-estimate the same regression using an unbalanced panel of 3009 households for 1971 and 1982 and report the results in

Columns 3 and 4 (of the 3009 unique households, only 1932 have data for both years, the rest only have 1971 data). Comparing the point estimates in Columns 1 and 2 to those in Columns 3 and 4, I find that the reduced form effects of bank access on HYV adoption are almost identical in magnitude between the balanced and unbalanced panel of households for 1971 and 1982. In Columns 5 and 6, I re-report my results from Columns 2 and 3 of Table 1.3 (i.e., my results using a balanced panel of 1404 households for 1971, 1982 and 1999). Further, I estimate equation 1.4 using an unbalanced panel of 3009 households for 1971, 1982 and 1999 and report the results in Columns 7 and 8. Comparing the point estimates in Columns 5 and 6 to those in Columns 7 and 8 suggest that my results are robust to using a balanced panel of households for 1971, 1982 and 1999. To summarize Table 1.6, I conclude that my results on the reduced form effects of bank access on HYV adoption are not sensitive to restricting my sample to a three-year balanced panel.

Second, I test whether attrition from the ARIS/REDS data set is correlated with the social banking policy variable. If households leaving the sample over time are systematically different from households who are present in all three years of the survey it would raise concerns about how to interpret my findings.[11] Table 1.7 shows the results of this analysis. The dependent variable in Columns 1 and 2 is the probability of a household leaving the sample in 1982 that equals 0 for every household in the year 1971, is equal to 0 if a household in the 1971 survey is also present in 1982, and it equals 1 if a household present in the 1971 survey leaves the sample in 1982. In my sample for 1971 and 1982, 1077 households present in the 1971 survey leave the sample in 1982. The dependent variable in Columns 3 and 4 is the probability of a household leaving the sample in 1982 and 1999 that equals 0 for

[11] To the extent that household attrition from the ARIS/REDS is correlated with the social banking policy variable, then the estimated results would not necessarily reflect the true effect of bank access on technology adoption, but rather something less general: the effect of bank access on technology adoption conditional on being in the sample.

every household in the year 1971, is equal to 0 if a household in the 1971 survey is also present in 1982 and 1999, and it equals 1 if a household present in the 1971 survey leaves the sample in 1982 and 1999. In my sample for the three survey years, 1605 households present in the 1971 survey leave the sample in 1982 and 1999. From Columns 1 and 2, I find that the social banking policy variable has no significant effect on the probability of a household leaving the sample in 1982. Further, the results in Columns 3 and 4 suggest that the social banking policy variable has no significant effect on the probability of a household leaving the sample in 1982 and 1999. To summarize the results from Table 1.7, I conclude that there is no selective attrition from the sample based on exposure to the social banking policy. The results from table 1.6 and 1.7 therefore both suggest that the effect of bank access on household HYV adoption (as shown in Table 1.3) are robust to the particular sample restrictions I impose.

To summarize Tables 1.3 and 1.4, I find that improving bank access significantly increases household adoption of HYV technology. Tables 1.5-1.7 show that these results are robust to controlling a contemporaneous policy (agricultural development program) as well as to addressing household attrition from the sample. Attrition turns out not to be related to the social banking policy, hence the results are same. The increase in HYV adoption due to social banking appears limited to the wealthiest and most educated households. This is consistent with social banking raising credit sufficiently to adopt HYV technology only for these groups, or access to credit not being the limiting factor in the household HYV adoption decision for less wealthy and less educated households.

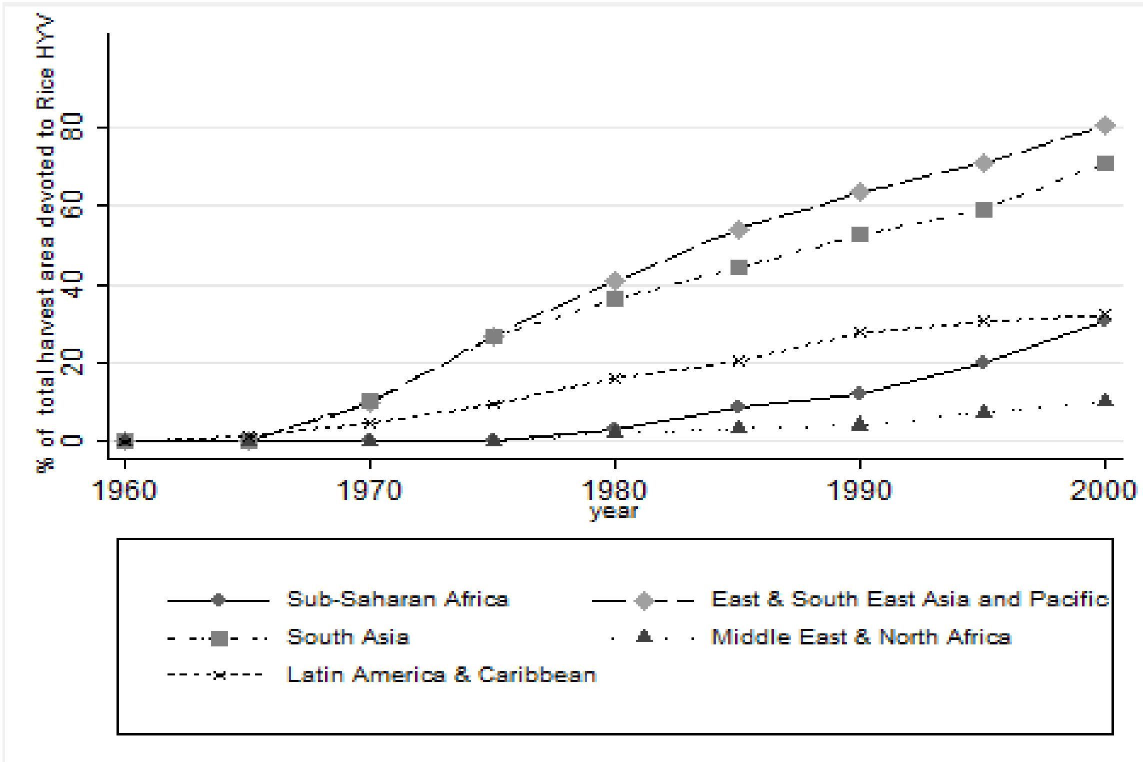
1.6 Conclusion

In this paper, I use the Indian social banking policy to provide exogenous variation in credit access and estimate its effect on the adoption of HYV technology. I find that increasing bank access increases the adoption of HYV technology. However, the effect is not uniform across households; in fact, the positive impact of bank access on technology adoption is restricted to households that are wealthier (in my analysis, the households in the top quartile of landholdings) and more educated (in my analysis, the households with heads that have more than primary schooling).

These results have important implications. On the one hand, my findings suggest that development of the formal financial markets could increase the rate of new technology adoption. While a number of studies have called attention to the importance of financial market development in economic development (Karlan and Morduch 2010), my paper highlights a new mechanism for this: through increasing technology diffusion. Comin and Hobijn (2010) suggest that increasing technology diffusion could significantly raise economic growth.

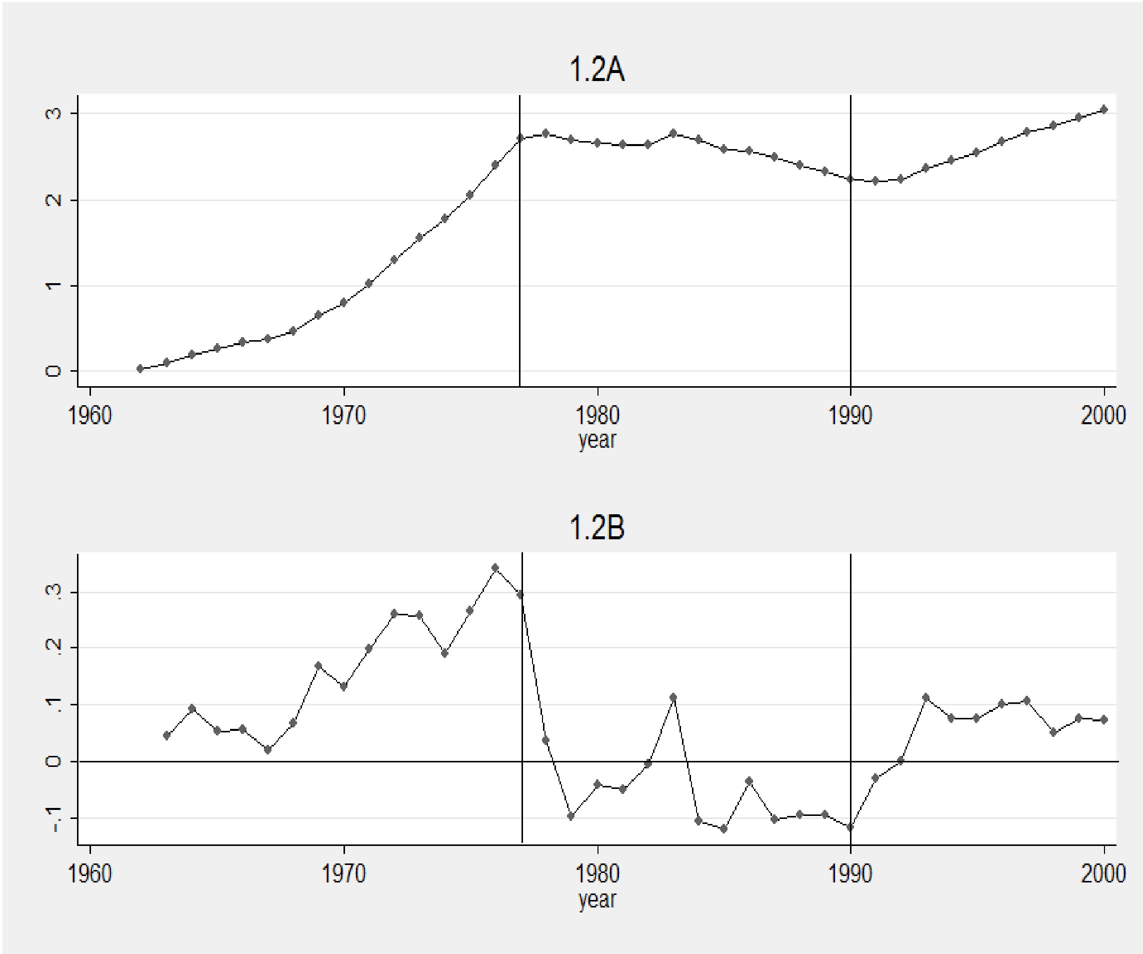
On the other hand, my findings suggest that not everyone's technology adoption decision is affected by expanding the formal banking system. While the wealthy and educated were more likely to adopt HYV when bank access improved, the poor and less educated were not impacted. These heterogeneous effects suggest that income inequality can be expected to rise if a country pursues a policy of expanding bank access to promote technology diffusion. Other studies have documented that the social banking program expanded credit across a broad set of households (Burgess, Pande and Wong 2005), so it is puzzling why the impacts on technology adoption were not experienced more broadly. One possibility that is still related to credit constraints is that the increase in credit access experienced by the poor and less educated was still inadequate to enable them to adopt the new technology (did the new loans go disproportionately to the wealthy and educated?). Another possibility is that the poor and the less educated face other barriers to HYV adoption that are decisive against HYV adoption. In future research I will attempt to disentangle the reasons for the heterogeneity in effects of bank access on new technology adoption.

Figure 1.1: Adoption of Rice HYV technology



Notes: Source: Evenson (2005)

Figure 1.2: Initial Financial Development and Bank Branch Growth



Notes: Figure 1.2A shows, for each year, the coefficient for the interaction term, financial development in 1961 and the dummy for that year. It is interpreted as the change in cumulative number of bank branches per capita in year t for a unit increase in financial development in 1961 (note the omitted year is 1961). Figure 1.2B shows the change in year-wise difference in cumulative number of bank branches per capita in year t for a unit increase in financial development in 1961. It shows the change in new branch openings per capita in year t for a unit increase in financial development in 1961 (note the omitted year is 1962-1961).

Table 1.1: Summary Statistics

Variable Name	mean	sd
Panel A.District panel data on banks (1961-2000)		
Number of bank branches per capita	0.65	0.55
Number of bank branches per capita in 1961	0.11	0.08
Population in 1961	1818721	1096267
log(state income in 1961)	6.74	0.16
log(number of rural locations per capita in 1961)	-0.44	0.39
log(population density in 1961)	2.75	0.59
Number of districts	93	
Number of observations	3720	
Panel B.ARIS/REDS Household panel data (1971,1982,1999)		
Used HYV	0.48	0.50
Land ownership in 1971 (in acres)	12.59	15.76
Household head with no education in 1971	0.59	0.49
Household head with primary education in 1971	0.26	0.44
Household head with above primary education in 1971	0.15	0.36
Age of household head	60.73	17.07
Number of bank branches per capita in 1961	0.10	0.08
log(state income in 1961)	6.75	0.14
log(number of rural locations per capita in 1961)	-0.49	0.43
log(population density in 1961)	2.65	0.56
Number of households	1404	
Number of observations	4212	

Notes: Panel B consists of households in ARIS/REDS data set who are in all three years. The households are farmers in 1971 mostly cultivating their own plots of land. Non-cultivators in 1971 are excluded from the sample. The district panel data on banks in Panel A is restricted to districts that are covered by ARIS/REDS dataset. Bank branch data are from Reserve Bank of India (2006). Data on state income are from Department of Statistics, Ministry of Planning, Government of India. Population and rural location data are from Census of India 1961.

Table 1.2: Impact of Social Banking Policy on Number of Bank Branches

	Number of bank branches per capita
Number of bank branches per capita in 1961*(1961-2000) trend	0.16^{***}
	(0.04)
Number of bank branches per capita in 1961*(1977-2000) trend	-0.18^{***}
	(0.05)
Number of bank branches per capita in 1961*(1990-2000) trend	0.12^{**}
	(0.05)
Post-1976 dummy*number of bank branches per capita in 1961	0.65^{***}
	(0.16)
Post-1989 dummy*number of bank branches per capita in 1961	-0.28^{**}
	(0.12)
District fixed effects	Yes
Year fixed effects	Yes
log(state income in 1961)* year fixed effects	Yes
log(population density in 1961)*year fixed effects	Yes
log(rural share in 1961) * year fixed effects	Yes
Observations	3720

Notes: Robust standard errors clustered by district are in parentheses. Bank branch data are from Reserve Bank of India (2006). Data on state income are from Department of Statistics, Ministry of Planning, Government of India. Population and rural location data are from Census of India 1961.

* Significant at 10-percent level.

** Significant at 5-percent level.

*** Significant at 1-percent level.

Table 1.3: Effect of Social Banking Policy on HYV Adoption

	(1)	(2)	(3)
Number of bank branches per capita in 1961* 1982 dummy	-1.22^{**}	-1.19^{**}	-1.18^{*}
	(0.59)	(0.57)	(0.68)
Number of bank branches per capita in 1961* 1999 dummy	-0.53	-0.41	-0.41
	(0.45)	(0.45)	(0.54)
Age of household head		0.00	0.01
		(0.00)	(0.01)
Age squared		-0.00	0.00
		(0.00)	(0.00)
Primary education in 1971		-0.01	
		(0.03)	
Primary education in 1971*1982 dummy		0.00	0.00
		(0.05)	(0.06)
Above primary education in 1971		0.05	
		(0.04)	
Above primary education in 1971*1982 dummy		-0.03	-0.03
		(0.05)	(0.06)
Second quartile of landownership in 1971		0.10^{***}	
		(0.03)	
Second quartile of landownership in 1971*1982 dummy		-0.01	-0.01
		(0.05)	(0.06)
Third quartile of landownership in 1971		0.14^{***}	
		(0.04)	
Third quartile of landownership in 1971*1982 dummy		-0.05	-0.05
		(0.05)	(0.05)
Fourth quartile of landownership in 1971		0.22^{***}	
		(0.04)	
Fourth quartile of landownership in 1971*1982 dummy		-0.09	
		(0.06)	
Fourth quartile landownership 71 low *1982 dummy			-0.09
			(0.07)
Fourth quartile landownership 71 middle*1982 dummy			-0.11
			(0.10)
Fourth quartile landownership 71 high*1982 dummy			0.04
			(0.14)

Table continues on next page

Table 1.3: Effect of Social Banking Policy on HYV Adoption (Continued)

	(1)	(2)	(3)
Village fixed effects	Yes	Yes	No
Household fixed effects	No	No	Yes
Year fixed effects	Yes	Yes	Yes
log(state income in 1961)* year fixed effects	Yes	Yes	Yes
log(population density in 1961)*year fixed effects	Yes	Yes	Yes
log(rural share in 1961) * year fixed effects	Yes	Yes	Yes
Number of households	1404	1404	1404
Observations	4212	4212	4212

Notes: The dependent variable in each regression is a dummy denoting household HYV adoption that equals 1 if the household has adopted HYV and is 0 otherwise. Robust standard errors clustered by district are in parentheses. The analysis uses household panel data from the ARIS/REDS, which is described in Panel B of Table 1.1 and in Section 1.4. In addition to the variables reported in the table, the specification in Columns 2 and 3 also control for interactions between landholding quartile and the 1999 dummy, and the specification in Column 3 adds household fixed effects and more detailed controls for household landholdings (specifically, it breaks Quartile 4 into three subcategories, and allows for year-specific effects of each subcategory). Mean 1971 landownership of households in Quartile 1, Quartile 2, Quartile 3 and Quartile 4 are 2.26 acres, 6.22 acres,11.88 acres and 31.31 acres respectively. Households in the fourth quartile of landownership are divided into 3 groups, low (16.4 to 25 acres), middle (26 to 50 acres) and high (above 50 acres) on the basis of their landownership.

* Significant at 10-percent level.

** Significant at 5-percent level.

*** Significant at 1-percent level.

Table 1.4: Heterogeneity in the Effect of Social Banking Policy on HYV Adoption by Initial Landholding and Education

	(1)	(2)	(3)	(4)
Number of bank branches per capita in 1961* 1982 dummy	-1.18^{*}	-0.94	-0.78	-0.60
	(0.68)	(0.85)	(0.63)	(0.84)
Number of bank branches per capita in 1961* 1999 dummy	-0.41	0.22	-0.24	0.32
	(0.54)	(1.05)	(0.51)	(1.03)
Number of bank branches per capita in 1961* 1982 dummy*second quartile of landownership in 1971		0.38		0.21
		(0.78)		(0.74)
Number of bank branches per capita in 1961* 1982 dummy*third quartile of landownership in 1971		-0.33		-0.40
		(0.82)		(0.81)
Number of bank branches per capita in 1961* 1982 dummy*fourth quartile of landownership in 1971		-1.92^{*}		-1.76^{*}
		(1.03)		(1.05)
Number of bank branches per capita in 1961* 1982 dummy*primary education in 1971			-0.86	-0.48
			(0.70)	(0.73)
Number of bank branches per capita in 1961* 1982 dummy*above primary education in 1971			-1.85^{**}	-1.41^{*}
			(0.90)	(0.84)
Age of household head	0.01	0.009*	0.01	0.009*
	(0.01)	(0.005)	(0.01)	(0.005)
Age squared	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Primary education in 1971*1982 dummy	0.00	-0.01	0.09	0.04
	(0.06)	(0.06)	(0.10)	(0.10)
Above primary education in 1971*1982 dummy	-0.03	-0.04	0.15	0.10
	(0.06)	(0.06)	(0.11)	(0.11)

Table continues on next page

Table 1.4: Heterogeneity in the Effect of Social Banking Policy on HYV Adoption by Initial Landholding and Education (Continued)

	(1)	(2)	(3)	(4)
Second quartile of landownership in 1971*1982 dummy	-0.01	-0.06	-0.03	-0.05
	(0.06)	(0.09)	(0.06)	(0.09)
Third quartile of landownership in 1971*1982 dummy	-0.05	-0.03	-0.06	-0.02
	(0.05)	(0.09)	(0.05)	(0.09)
Fourth quartile of landownership in 1971 low*1982 dummy	-0.09	0.12	-0.10	0.09
	(0.07)	(0.12)	(0.07)	(0.13)
Fourth quartile of landownership in 1971 middle*1982 dummy	-0.11	0.09	-0.12	0.06
	(0.10)	(0.14)	(0.10)	(0.15)
Fourth quartile of landownership in 1971 high*1982 dummy	0.04	0.24	0.03	0.21
	(0.14)	(0.17)	(0.14)	(0.17)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
log(state income in 1961)* year fixed effects	Yes	Yes	Yes	Yes
log(population density in 1961)*year fixed effects	Yes	Yes	Yes	Yes
log(rural share in 1961) * year fixed effects	Yes	Yes	Yes	Yes
Number of households	1404	1404	1404	1404
Observations	4212	4212	4212	4212
Effect [p-value of effect] for:				
Households in first quartile of landownership in 1971		-0.94		-0.60
		[0.273]		[0.475]
Households in second quartile of landownership in 1971		-0.56		-0.39
		[0.351]		[0.472]
Households in third quartile of landownership in 1971		-1.27^{**}		-1.00
		[0.048]		[0.105]
Households in fourth quartile of landownership in 1971		-2.86^{***}		-2.36^{**}
		[0.001]		[0.015]
Households with illiterate head in 1971			-0.78	-0.60
			[0.216]	[0.475]
Households with primary-educated head in 1971			-1.64^{**}	-1.08
			[0.026]	[0.354]
Households with above primary-educated head in 1971			-2.63^{***}	-2.01^{**}
			[0.003]	[0.028]

Notes: The dependent variable in each regression is a dummy denoting household HYV adoption that equals 1 if the household has adopted HYV and is 0 otherwise. Robust standard errors clustered by district are in parentheses. Column 1 repeats the specification of Table 1.3, Column 3. Column 2 allows the effect of social banking to vary by landholding category (the omitted group is the households in the bottom quartile of landholdings). Column 3 allows the effect of social banking to vary by educational attainment category (the omitted group is the households with illiterate household heads). Column 4 allows for heterogeneity in effect by both landholdings and education. The bottom panel of the table shows the effect of social banking on HYV adoption for the 4 land quartiles and the 3 education categories (and are calculated based on the coefficients reported in the upper panel); the p-value associated with the null hypothesis that the effect of social banking is zero for the category of household is reported in brackets below.

* Significant at 10-percent level.

** Significant at 5-percent level.

*** Significant at 1-percent level.

Table 1.5: Robustness Check-Controlling for Agricultural Development Programs

	(1)	(2)	(3)	(4)
Number of bank branches per capita in 1961* 1982 dummy	-1.16^{*}	-0.87	-0.78	-0.57
	(0.65)	(0.82)	(0.60)	(0.82)
Number of bank branches per capita in 1961* 1999 dummy	-0.42	0.18	-0.24	0.30
	(0.54)	(1.09)	(0.51)	(1.05)
Number of bank branches per capita in 1961* 1982 dummy*second quartile of landownership in 1971		0.32		0.18
		(0.74)		(0.72)
Number of bank branches per capita in 1961* 1982 dummy*third quartile of landownership in 1971		-0.40		-0.45
		(0.79)		(0.80)
Number of bank branches per capita in 1961* 1982 dummy*fourth quartile of landownership in 1971		-1.95^{*}		-1.79^{*}
		(0.99)		(1.03)
Number of bank branches per capita in 1961* 1982 dummy*primary education in 1971			-0.87	-0.48
			(0.68)	(0.71)
Number of bank branches per capita in 1961* 1982 dummy*above primary education in 1971			-1.71^{*}	-1.28
			(0.95)	(0.91)

Notes: The dependent variable in each regression is a dummy denoting household HYV adoption that equals 1 if the household has adopted HYV and is 0 otherwise. Robust standard errors clustered by district are in parentheses. Columns 1-4 in Table 1.5 use the same specifications as in Columns 1-4 in Table 1.4 except that I add the year-specific effects of a dummy indicating that the household lives in a village covered by the Intensive Agricultural Development Program (IADP) in 1971, and a dummy indicating that the household lives in a village covered by the Intensive Agricultural Area Program (IAAP) in 1971.

* Significant at 10-percent level.

** Significant at 5-percent level.

*** Significant at 1-percent level.

Table 1.6: Effect of Social Banking Policy on HYV Adoption (Balanced vs Unbalanced Panel)

	Balanced 1971 and 1982		Unbalanced 1971 and 1982		Balanced 1971, 1982, 1999		Unbalanced 1971, 1982, 1999	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of bank branches	-0.97^{**}	-0.97	-0.98^{**}	-0.95	-1.19^{**}	-1.18^{*}	-1.16^{**}	-1.16
per capita in 1961*1982 dummy	(0.48)	(0.67)	(0.48)	(0.75)	(0.57)	(0.68)	(0.55)	(0.78)
Number of bank branches					-0.41	-0.41	-0.38	-0.39
per capita in 1961*1999 dummy					(0.45)	(0.54)	(0.48)	(0.63)
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls*1982 dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls*1999 dummy					Yes	Yes	Yes	Yes
Village fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Household fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(state income in 1961)* year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(population density in 1961)* year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(rural share in 1961)* year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households	1932	1932	3009	3009	1404	1404	3009	3009
Observations	3864	3864	4941	4941	4212	4212	5817	5817

Notes: The dependent variable in each regression is a dummy denoting household HYV adoption that equals 1 if the household has adopted HYV and is 0 otherwise. Robust standard errors clustered by district are in parentheses. The analysis uses household panel data from the ARIS/REDS, which is described in Panel B of Table 1.1 and in Section 1.4. The specification in columns 1 and 2 represent a balanced panel for the years 1971 and 1982 where 1932 households are present in both the survey years 1971 and 1982. The specification in columns 3 and 4 represent an unbalanced panel for the years 1971 and 1982 where 1077 households present in the 1971 survey do not appear in 1982. The specification in columns 5 and 6 represent a balanced panel for the years 1971, 1982 and 1999 where 1404 households are present in all three survey years 1971, 1982 and 1999. The specification in columns 7 and 8 represent an unbalanced panel for the years 1971, 1982 and 1999 where 1605 households present in the 1971 survey do not appear in 1982 and 1999.*, **, *** Significant at the 10 percent, 5 percent, and 1-percent level, respectively.

Table 1.7: Effect of Social Banking Policy on Sample Attrition

	Prob(leave sample in 1982) (1)	Prob(leave sample in 1982) (2)	Prob(leave sample in 1982 and 1999) (3)	Prob(leave sample in 1982 and 1999) (4)
Number of bank branches per capita in 1961* 1982 dummy	0.10 (0.22)	0.11 (0.31)	0.33 (0.29)	0.33 (0.35)
Number of bank branches per capita in 1961* 1999 dummy			0.35 (0.29)	0.35 (0.35)
Household Controls	Yes	Yes	Yes	Yes
Household Controls* 1982 dummy	Yes	Yes	Yes	Yes
Household Controls* 1999 dummy			Yes	Yes
Village fixed effects	Yes	No	Yes	No
Household fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
log(state income in 1961)* year fixed effects	Yes	Yes	Yes	Yes
log(population density in 1961)* year fixed effects	Yes	Yes	Yes	Yes
log(rural share in 1961)* year fixed effects	Yes	Yes	Yes	Yes
Number of households	3009	3009	3009	3009
Observations	6018	6018	9027	9027

Notes: The dependent variable in each regression is a dummy denoting the probability of leaving the sample which equals 1 if the household leaves the sample in a given year and 0 otherwise. The mean and standard deviation of the dependent variable in Columns 1 and 2 are 0.18 and 0.38 respectively. The mean and standard deviation of the dependent variables in Columns 3 and 4 are 0.36 and 0.48 respectively. Robust standard errors clustered by district are in parentheses. Columns 1 and 2 are estimated using unbalanced panel data for years 1971 and 1982. Columns 3 and 4 are estimated using an unbalanced panel for years 1971, 1982 and 1999. Household controls are the same as used in Table 1.3, columns 2 and 3. *, **, *** Significant at the 10 percent, 5 percent, and 1-percent level, respectively.

Chapter 2

Access to Formal Banks and New Technology Adoption: Evidence from Indian Districts

2.1 Introduction

The objective of this paper is to analyze the effect of formal bank access on new technology adoption in India. Technological innovation is key to economic development and in sustaining high living standards around the world. Therefore, delays in technology adoption are puzzling in an environment where people know new technologies to be better than existing technologies. Hence it is important to analyze what causes these delays in technology adoption.

A large literature explores the determinants of new technology adoption. Although credit constraints have been mentioned as a potential barrier to adoption (e.g., Croppenstedt et al. 2003; Sunding and Zilberman, 2001; Barret et al., 2003; Feder and O'Mara, 1981), there is very little empirical evidence on the impact of access to credit on technology. The only existing study I am aware of that rigorously estimates the impact of formal credit access on new technology adoption is Mukherjee (2012), which uses shifts in bank branching policy in India and Additional Rural Incomes Survey (ARIS) and Rural Economic and Demographic Survey (REDS) Indian household panel data to identify the causal effect of bank access on HYV seed adoption. This study provides new empirical evidence on the question by applying the same identification strategy as Mukherjee (2012) to a different dataset: a 1967-1987 panel data set on Indian districts with agricultural variables from the Evenson and McKinsey India Agriculture and Climate dataset, and bank branch data from the Reserve Bank of India. Though this data is at a more aggregate level (district level rather than household level), it is more comprehensive in several respects. This dataset covers all of India (while the ARIS/REDS data covers only a sample of districts in India), contains more years of data (the ARIS/REDS has observations for three years, 1971, 1982 and 1999), and has a more inclusive measure of HYV use (it has acreage under HYV cultivation, which captures both the intensive and extensive margins of HYV seed adoption).

It is difficult to identify the causal effect of bank access on HYV technology adoption. Bank location decisions depend on factors like population density, unmet demand for credit and some of these factors could affect HYV adoption. Therefore, correlations between bank access and HYV adoption is unlikely to have a causal interpretation. Hence, I use district-time variation in bank access generated by policy shifts regarding bank branching in India to estimate the causal effect of bank access on district HYV adoption. As in Mukherjee (2012), I follow the empirical strategy used by Burgess and Pande (2005) to study the role of bank access on technology adoption. Between 1977-1990, the Central Bank of India implemented a 1:4 branch licensing policy that required banks to open 4 branches in unbanked locations in order to open a branch in an already banked location. This policy was enforced to attain the Indian governments' objective of improving bank access in financially less developed areas. However, banks were largely unconstrained to choose their locations before 1977 and after 1990. This "social banking policy" led to a tremendous increase in new branch openings in financially less developed areas during 1977-1990.

Using data on district-level HYV use in India I implement my differences-in-differences strategy where I estimate the change in HYV adoption before and after the social banking period between more and less financially developed districts. I find that there was a significant increase in HYV adoption in financially less developed districts during the social banking period. Additionally, taking advantage of the multiple years of pre-social banking policy data, I am able to perform placebo tests exploring the validity of the parallel trend assumption which underlies the interpretation of the difference-in-differences estimate as the causal effect of social banking.[1] Difference-in-differences estimates obtained comparing pairs of "before" years, with one of the years coded as pseudo-treated to the policy, are not significantly different from zero. Thus there is no evidence of differential trends in HYV use between districts with higher and lower initial financial development in the years preceding the social banking period, which raises the validity of the parallel trend assumption. This is an important result that enables me to interpret the difference-in-differences estimates obtained in this paper, as well as Mukherjee (2012), as the effect of the social banking policy.

The paper is organized as follows. In the next section I provide some background on HYV technology. I describe my empirical strategy in Section 2.3. After the describing my data in section 2.4, I explain my results in section 2.5. Section 2.6 concludes.

[1] Mukherjee (2012) is unable to provide such placebo tests because there is only one year of pre-policy data in the ARIS/REDS dataset.

2.2 Background

HYV seeds were introduced in a number of developing countries including India in the mid-1960's to improve agricultural productivity and attain self-sufficiency in food production. The use of HYV seed varieties, combined with the expanded use of fertilizers and pesticides, irrigation led to a substantial increase in agricultural output in a number of countries beginning in the late-1960's. Specifically, areas with good irrigation systems and better developed infrastructure experienced a phenomenal increase in agricultural productivity immediately after the adoption of HYV seeds. This phenomenal increase in agricultural production due to HYV seed adoption was characterized as a "Green Revolution".

The HYV seeds were shorter than normal height that made them less prone to falling down under heavy doses of fertilizer. They also had a higher grain to straw ratio compared to traditional seed varieties that produced more output. HYV seeds grew more quickly than traditional varieties, thereby permitting farmers to practice multiple cropping on their land and increase agricultural output. Despite these potential advantages, HYV seed cultivation required stable access to water and a more intensive use of fertilizers and pesticides. Therefore, farmers could benefit from using HYV seeds only if they were able to finance the upfront costs of irrigation and higher working capital requirements of using fertilizers and pesticides. Hence, farmers living in areas with better developed irrigation systems and access to complementary inputs for HYV seed cultivation were likely to be the initial adopters of HYV seed varieties.

Evenson (2005) documents considerable regional variation in the diffusion of HYV technology over time. While some of these differences in the spread of HYV technology are related to differences in environmental conditions, other factors (for e.g., credit access, education) may also affect the diffusion of HYV technology. Hence it is a question why the

HYV seed technology did not spread faster.

Zhang et al. (2002), using district panel data from India covering 280 districts for 25 years, show that the overall share of cropped area planted under HYV seeds increased from 17 percent in 1970 to 44 percent in 1985 and to 59 percent in 1995. They show that there exists substantial regional variation in HYV adoption rates between Indian states. These differences in adoption rates can be partly attributed to varying agro-ecological conditions and differences in rural infrastructure. The observation that differences in rural infrastructure affect HYV adoption suggest a possible role for bank access in HYV adoption, as investments in infrastructure may have greater complementarity in production with HYV seeds than traditional varieties.

Rural financial markets in India were dominated by informal lending institutions since independence in 1947. In response to the prevailing conditions in the rural financial markets, the Government of India set out a program to improve access to formal financial opportunities in rural India. First, the government nationalized 14 largest commercial banks in 1969. Following nationalization, the government launched a branch expansion program to improve bank access in rural areas. As a part of the program, the government adopted a social banking policy between 1977-1990 that led to a tremendous increase in bank access in financially less developed areas during that period. I use shifts in this policy over time to examine the effect of bank access on district HYV adoption.

2.3 Empirical Strategy

Identifying the causal effect of bank access on HYV technology adoption is difficult because bank access can be potentially endogenous. Since banks do not choose where to locate on a random basis, simple regressions of HYV technology adoption on bank access will in general not provide the causal effect of bank access on HYV adoption. To address the endogeneity problem, I exploit district-time variation in the new bank branch openings induced by shifts in India's policies regarding bank branching.

In 1969, the 14 largest commercial banks of India were nationalized. After nationalization, the Indian government embarked on a bank branch expansion program that intended to equalize bank access across Indian states. The Indian Central Bank, which is called the Reserve Bank of India, made a list of unbanked locations meeting a certain population cutoff that were to be targeted for new branch openings. As the same population cutoff was applied across India, regions with a lower initial stock of bank branches per capita were likely to be the primary targets of new branch openings. This bank expansion program was not effective in improving equity in bank access–banks apparently did not have much incentive to open new branches in less financially developed areas–thus in 1977 the Reserve Bank of India shifted to a more aggressive policy. The new branch licensing policy required banks to open 4 branches in unbanked locations in order to open one branch in an already banked location (this is sometimes called the 1:4 branch licensing policy; following Burgess and Pande (2005), I will also refer to it as the social banking policy). Further, to ensure that the banks served the locations where they opened new branches (rather than operating phantom branches with no real lending activity), the Reserve Bank of India required branches to maintain a credit-deposit ratio of 60 percent within their geographical area of operation. The social banking policy was discontinued in 1990. However, banks were not allowed to close if a branch was the only one serving in a particular location, and thus banks that were bound by the social banking policy to open branches in less financially developed areas typically had to maintain those branches even after the discontinuation of social banking. But after 1990, banks were once again free to locate new branches where they wished, as they had been able to do prior to 1977.

Burgess and Pande (2005) use the adoption and discontinuation of the social banking policy to identify the causal effect of bank access on rural poverty in India. They use state panel data and take advantage of the fact that the social banking policy increased bank access more for states that were initially less financially developed than states that were more financially developed. I apply their identification strategy to a different outcome—HYV technology adoption at the district level—and use district-time rather than state-time variation in exposure to social banking. This is a difference-in-differences identification strategy—essentially, I take the change over time in HYV adoption among districts with lower initial financial development, then I subtract out the change over time in HYV adoption among districts with higher initial financial development—to remove the secular change over time and recover the causal effect of social banking. The following equation describes this:

$$HYVuse_{dt} = \alpha_d + \beta_t + \gamma(B_{d1961} * SocialBankingPeriod_t) + \pi * X_{dt} + e_{dt} \tag{2.1}$$

where $HYVuse_{dt}$ is the area under HYV cultivation (in 1000's of hectares) in district d at time t. B_{d1961} is initial financial development of a district (measured as the number of bank branches per capita in a district in 1961). The Social Banking Period is a dummy variable indicating if the year falls between 1977-1990. X_{dt} are district or state characteristics. α_d are district fixed effects and β_t are year fixed effects.

The parameter of interest is γ, the difference-in-differences in HYV use. Under the parallel trend assumption; i.e., without social banking, the change over time in HYV use in less financially developed areas would have been the same as the change in more financially developed areas-this gives the causal effect of social banking. (As a technical matter, it gives the *negative* of the effect of social banking because it is the less financially developed areas that receive more new bank branches under social banking.) It is plausible that less financially developed areas are less developed in other respects as well, so we might also be concerned that they might have been slower to adopt new technologies (or, faster, in the case of mean reversion). To mitigate this concern, I always control for year-specific effects of initial state income, population density and rural share on HYV seed adoption. Additionally, I will assess the validity of the parallel trend assumption by estimating year-specific effects of initial financial development and testing whether the difference-in-difference between two pre-Social Banking Policy years is zero. That is, I estimate the following equation:

$$HYVuse_{dt} = \alpha_d + \beta_t + \gamma_t(B_{d1961}) + \pi * X_{dt} + e_{dt} \tag{2.2}$$

with 1976 as the omitted year, so the γ_t gives the change in HYV use between year t and 1976 for a one unit increase in financial development in 1961.[2] Because the social banking period did not begin until 1977, then 1976 and earlier years precede the policy, and the γ_t for t $\ll$ 1976 would not reflect any effects of the policy; thus comparisons of two pre-policy years are placebo experiments. To the extent that these estimates were different from zero, it would be indicative of pre-existing differential trends by initial financial development. On the other hand, if these estimates were not different from zero, it would lend confidence in the parallel trend assumption, and make it possible to interpret the γ_t for t$\gg$ 1976 as the causal effects of the social banking policy.

[2]In other words, we might think of γ_t as the change in HYV use between year t and 1976 in some district minus the change in HYV use over the same period in a district with a one unit lower initial financial development.

2.4 Data

The primary data source for my empirical analysis is the Evenson and McKinsey India Agriculture and Climate data set that has data on crop area and land use at the district level over time. I obtain this data from the Duflo and Pande "Dams"(2007) dataset. The India Agriculture and Climate data set uses government publications (for e.g. Area under Production of Principal Crops in India) to form its agricultural database. Detailed data on crop area are obtained from cadastral surveys done by village revenue agencies in the states. As many as 271 districts, covering 13 major states in India, constitute the database. Area-wise, the database covers more than 85 percent of India with the exception of the southern state of Kerala and the north-eastern state of Assam. Other areas not covered by the dataset are relatively some of the least important from the agricultural perspective. The dataset is longitudinal and it has information on the area under HYV cultivation (in 1000's of hectares) beginning 1966. Thus my sample comprises a balanced panel of 258 districts over the time period 1967-1987. This dataset is helpful for implementing my empirical strategy as I have HYV use data before (pre-1977) and after (post-1977) the enforcement of the social banking policy. More importantly, the variable area under HYV cultivation enables me to analyze both the intensive and extensive margins of HYV technology adoption at the district level. That is, it reflects not just the number of farmers using the HYV technology at all, but also how much they are using it.

For measuring bank access in districts, I use bank branch data from the Reserve Bank of India. Based on the location, year opened information for each bank branch, and district-wise population counts from Census of India 1961, I form a variable for all districts that measures the number of bank branches in 1961 per 10,000 persons in 1961, and captures the district's initial financial development. In the paper I refer to bank branches per 10,000 persons as bank branches per capita.[3]

In order to form the measure of initial financial development, and in order to merge this variable into the district HYV use dataset (which is based on the 1961 district definitions), I had to contend with the fact that many districts in India underwent major boundary changes between 1961 and 2000. Since I use the 1961 census population to construct the measure of initial financial development, I persist with the 1961 district definitions to form a consistent measure of the variable. I use information from the India Administrative Atlas tables, published by the Census of India, and from Kumar and Somanathan (2009) to code the district boundary changes for the districts appearing in my district HYV use sample. For the districts that had complex boundary changes, I use population apportionment to form a measure of initial financial development that is consistent with the 1961 district definitions.

I also use several state-level variables in my analysis to control for some potential differential trends: state income, population density, and number of rural locations, all measured in 1961. I obtain these variables from Burgess and Pande (2005). The original data source for state income is the Department of Statistics, Ministry of Planning, Government of India, and for population density and number of rural locations is the 1961 Census of India. Table 2.1 shows the means and standard deviations of the variables used in the empirical analysis below.

[3] Burgess and Pande (2005) use number of bank branches in 1961 per 10,000 persons in the state for their measure of initial financial development, and I apply their definition to the district level.

2.5 Results

In Table 2.2, I present the results of estimating Equation 2.1. Column 1 shows that there was a significant increase in the area under HYV cultivation for initially financially less developed districts during the social banking period. The financially less developed districts experienced a tremendous increase in bank access during the social banking period as discussed in Section 2.3, and documented by Burgess and Pande (2005) and Mukherjee (2012). Thus the Column 1 finding is consistent with increased bank access increasing district HYV use.

Next, I allow the effects of initial financial development to differ by year. That is, I estimate Equation 2.2. As explained in Section 2.3, examining the pattern of coefficients for the pre-social banking policy years comprises a placebo experiment. In Figure 2.1, I display the year-specific effects of initial financial development on district HYV adoption where the dependent variable is Area under HYV cultivation (in 1000's of hectares). The coefficients in Figure 2.1 reveal that differences in HYV adoption over time in more financially developed districts were not different from similar differences in less financially developed districts before 1976, which is supportive of the parallel trend assumption. Further, the year-wise coefficients suggest that the initially financially less developed districts did not start adopting HYV technology immediately after the social banking policy was implemented in 1977. Bank access seems to significantly increase area under HYV cultivation in financially less developed districts from the early 1980's. (As discussed before, the coefficient γ in equation 2.2 captures the *negative* of the effect of social banking because it is the less financially developed districts that received more bank access during the social banking period.)

One plausible story explaining this result may be that banks responded to the social banking policy with a lag, building new branches rigorously in financially less developed areas from the early 1980's and not before. Another plausible story may be that households took time to adjust to the newly offered banking services, and expansion of new branches in an area were not associated with an immediate increase in lending activities. However, I cannot distinguish between the two hypothesis because they make the same prediction.

I proceed by estimating the reduced form effects of initial financial development on district HYV adoption using $log(HYVuse_{dt})$ as the dependent variable in equation 2.1 (where $HYVuse_{dt}$ is the Area under HYV cultivation in 1000's of hectares). In Table 2.2, Column 3, I show that bank access had no significant effect on district HYV adoption with $log(HYVuse_{dt})$ as the dependent variable. I re-estimate equation 2.2 using $log(HYVuse_{dt})$ as the dependent variable and plot the year-wise coefficients of initial financial development in Figure 2.2. Figure 2.2, shows the year-to-year differences in the percentage of area devoted to HYV use for a unit increase in initial financial development. Change in the percentage of cultivable area devoted to HYV seeds over time do not seem to differ between more and less financially developed districts before the enforcement of the social banking policy in 1977. The year-specific coefficients turn negative beginning early 1980's, suggesting that the percentage of area devoted to HYV seeds increased in the financially less developed districts during the social banking period, although the effects are not significant.

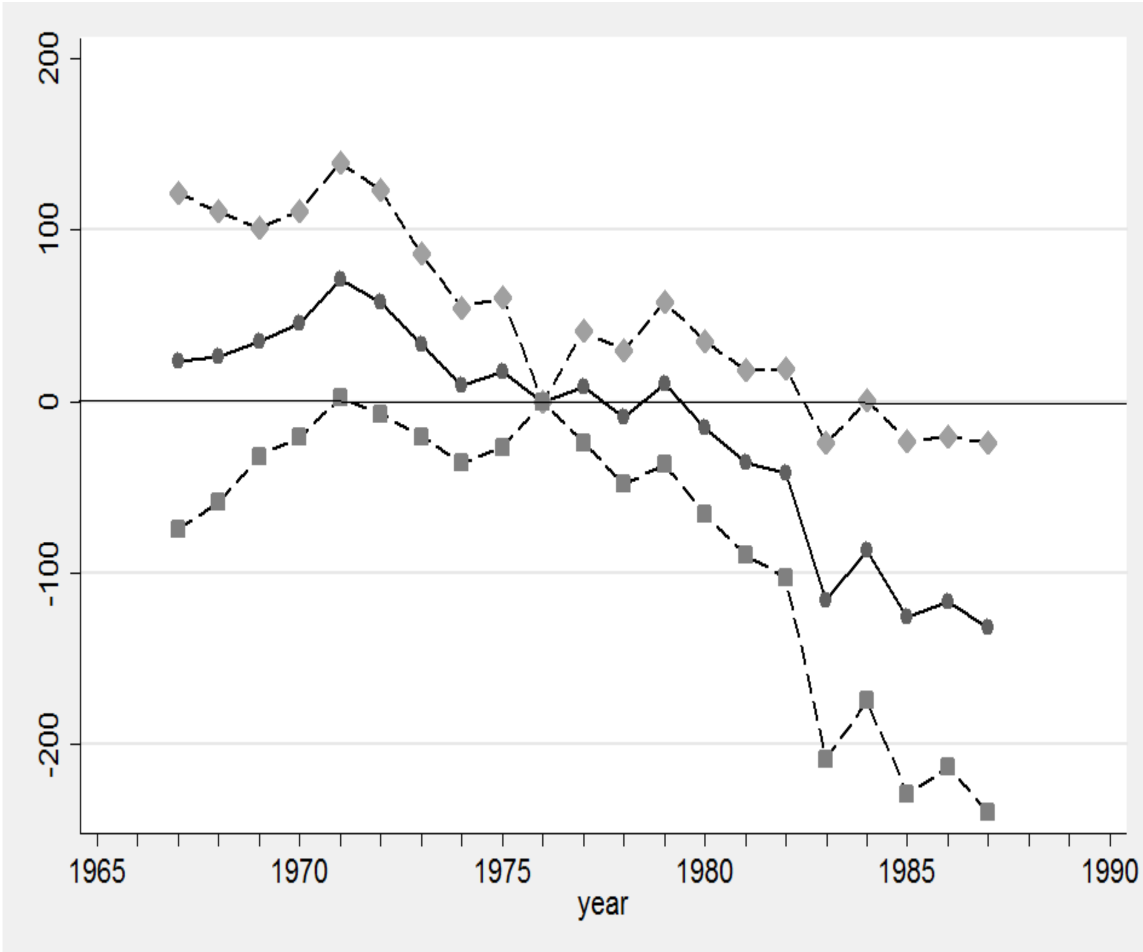
Guided by Figures 2.1 and 2.2, where the reduced-form effects were around zero early in the social banking period and subsequently became more negative, I modify equation 2.1 to allow the effect of social banking to differ between an earlier period and later period. In particular, I divide the 1977-1987 period into two periods depicting an early (1977-1981) and late (1982-87) social banking period. We already know from the graphs that the point estimates will be different, and the purpose of restricting the year-wise effects there to just effects is two-fold. First, by pooling multiple after years, the estimates will be more precisely estimated, permitting more powerful hypothesis testing. Second, they provide a simple summary of the year-wise estimates in the graph, i.e., the average effect for the early period and the average effect for the later period. In Table 2.2, Column 2, I find that the area under HYV cultivation increased in financially less developed districts in both the early and late stages of the social banking period, but the effect in the later stage is considerably larger and is significant at the 5 percent level. An F-test rejects the equality of the early period impact and late period impact at the 5 percent level of significance. Column 4 shows that log(area under HYV cultivation) increased in financially less developed districts in both the early and late stages of the social banking period, but neither effect is significant. An F-test rejects the equality of the early period impact and late period impact at the 1 percent level of significance.

2.6 Conclusion

In this paper, I use the Indian social banking policy to provide exogenous variation in credit access and estimate its effect on the adoption of HYV technology in Indian districts. I find that increase in bank access affected district HYV adoption through increase in the area under HYV cultivation. However, the effect of the social banking policy on district HYV adoption was not immediate, and it is only in the later stages of the social banking period that I find a significant effect. One possible explanation for this observed timing of effects may be that banks responded to the social banking policy with a lag, while another may be that households took time to respond to the newly offered banking services.

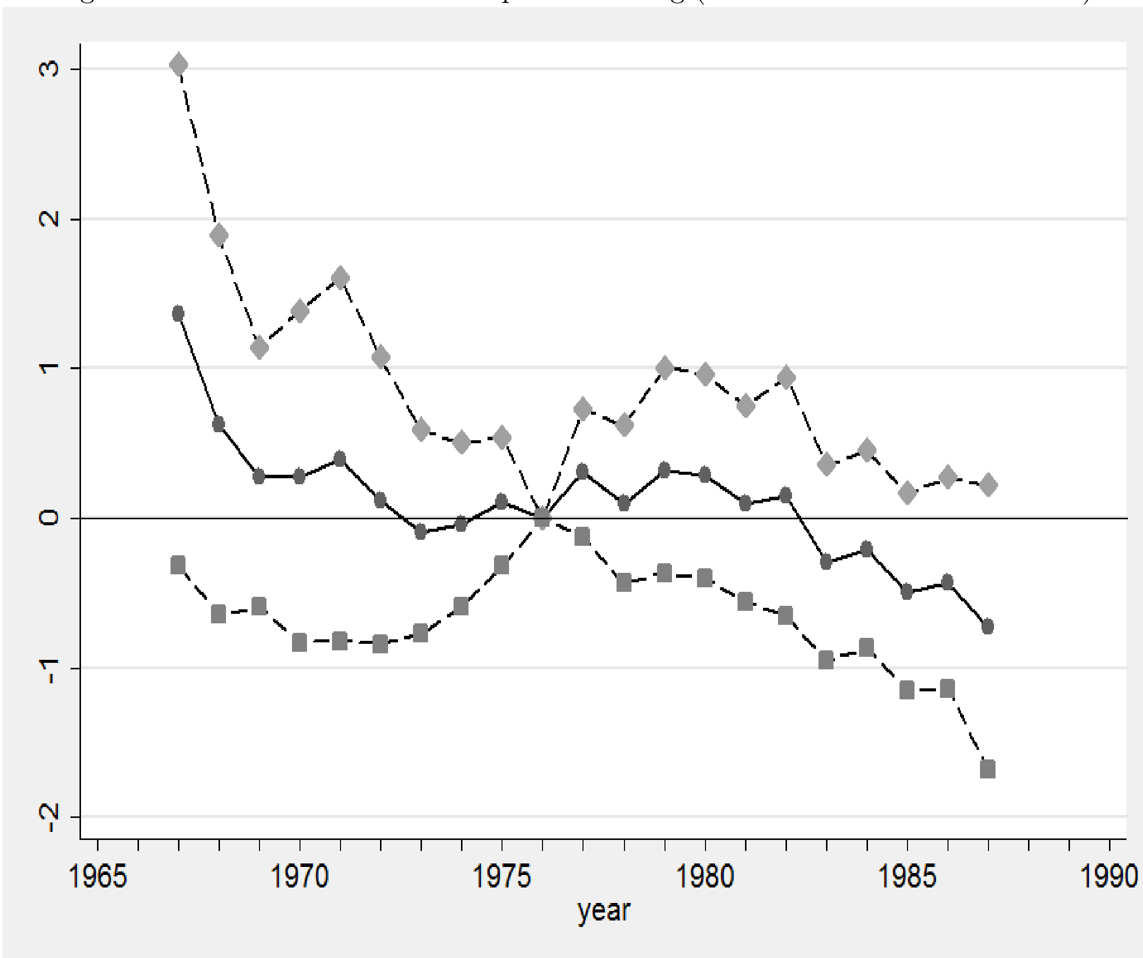
These results have important implications. My findings suggest that access to formal financial markets could increase the rate of technology adoption. While a number of studies have emphasized the role of financial market development in economic development (Karlan and Morduch 2010), this paper along with Mukherjee (2012) are the first to document that one of the ways financial development impacts economic development is through increasing technology diffusion. Comin and Hobijn (2010) suggest that increasing technology diffusion could significantly raise economic growth.

Figure 2.1: Initial Financial Development and Area Under HYV Cultivation



Notes: Figure 2.1 shows, for each year, the coefficient for the interaction term, financial development in 1961 and the dummy for that year. It is interpreted as the change in area under HYV cultivation (in 1000's of hectares) in year t for a unit increase in financial development in 1961 (note the omitted year is 1976). The dashed lines represent the 95 percent confidence intervals.

Figure 2.2: Initial Financial Development and log (Area Under HYV Cultivation)



Notes: Figure 2.2 shows, for each year, the coefficient for the interaction term, financial development in 1961 and the dummy for that year. It is interpreted as the change in the percentage of area under HYV cultivation in year t for a unit increase in financial development in 1961 (note the omitted year is 1976). The dashed lines represent the 95 percent confidence intervals.

Table 2.1: Summary Statistics

Variable Name	mean	sd
Area under HYV cultivation (in 1000's of hectares)	112.06	114.12
log (Area under HYV cultivation)	4.14	1.26
Number of bank branches per capita in 1961	0.09	0.08
Population in 1961	1451479	864992
log(state income in 1961)	6.74	0.15
log(number of rural locations per capita in 1961)	-0.53	0.44
log(population density in 1961)	2.66	0.57
Number of districts	258	
Number of observations	5414	

Notes: The district data on HYV use is from the Evenson and McKinsey India agriculture and climate data set for the years 1967-1987. Bank branch data are from Reserve Bank of India (2006). Data on state income are from Department of Statistics, Ministry of Planning, Government of India. Population and rural location data are from Census of India 1961.

Table 2.2: Effect of Social Banking Policy on District HYV Cultivation

	Area Under HYV Cultivation (1)	Area Under HYV Cultivation (2)	log (Area Under HYV Cultivation) (3)	log (Area Under HYV Cultivation) (4)
Number of bank branches per capita in 1961*(1977-1987)	-91.85^{**} (41.52)		-0.39 (0.46)	
Number of bank branches per capita in 1961*(1977-1981)		-39.89 (30.82)		-0.08 (0.40)
Number of bank branches per capita in 1961*(1982-1987)		-135.15^{**} (55.30)		-0.64 (0.52)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
log(state income in 1961)* year fixed effects	Yes	Yes	Yes	Yes
log(population density in 1961)* year fixed effects	Yes	Yes	Yes	Yes
log(rural share in 1961)* year fixed effects	Yes	Yes	Yes	Yes
Observations	5414	5414	5414	5414

Notes: Robust standard errors clustered by district are in parentheses. Area under HYV cultivation (in 1000's of hectares) is from the Evenson and McKinsey India Agriculture and Climate dataset. Bank branch data are from Reserve Bank of India (2006). Data on state income are from Department of Statistics, Ministry of Planning, Government of India. Population and rural location data are from Census of India 1961.

* Significant at 10-percent level.

** Significant at 5-percent level.

*** Significant at 1-percent level.

Chapter 3

How Do Politicians Save? Buffer Stock Management of Unemployment Insurance Finance (with Steven Craig, Wided Hemissi and Bent Sorensen)

3.1 Introduction

The objective of the research in this paper is to develop and test a model of how state governments adjust their stock of savings in response to economic cycles. We present a series of empirical tests using the U.S. Unemployment Insurance (UI) system that suggest, for a case where the motivation for government savings accounts is clear, that a buffer stock model balancing impatience with risk aversion is an excellent description of government behavior. The recent economic downturn has spurred thinking about how governments might manage resources that could be used to smooth government consumption. Governments, however, are not the same as households, and consumption models cannot be seamlessly used to model governments. For example, the political economy/public choice perspective on government behavior would question whether in fact governments are able to save, even if they desired to do so, if politicians are systematically more impatient than residents.[1] Further, the Ricardian view would suggest that government savings or borrowing would be completely offset by households, in which case there would be no aggregate effect on savings or debt in the economy, and thus there would be no reason for the time path of government expenditures to fluctuate with the economy. Thus, to study how governments behave with respect to savings, we model state government management of UI savings accounts as an example of a government program that is explicitly designed to smooth economic fluctuations, and one for which there is likely to be private market failure so that systematic offsetting household behavior is unlikely.

The UI program in the U.S. allows considerable latitude for individual states to adjust all four key program elements; benefit levels paid to unemployed individuals, the eligibility criteria for receipt by individuals, taxes levied on firms, and the level of UI trust fund savings. UI has the further advantage that each state maintains its system under a federal programmatic umbrella, which means the structure is similar between states despite significant policy differences. Further, UI addresses an actual market failure problem since insurance markets are faced with asymmetric information between buyers and sellers, which at least suggests a rationale for state governments to maintain an insurance-type reserve

[1] That is, if politicians are better off by spending any saved resources now, and they are not penalized for being "short-sighted," then their incentives will prevent effective savings.

fund (Rothschild & Stiglitz, 1977). In the U.S. state governments maintain an explicit UI savings account called the UI Trust Fund, financed by an earmarked tax on firms, and make payments to unemployed workers only out of the UI Trust Fund. The institutional structure therefore makes feasible smoothing behavior over time, such as would be consistent with a Barro tax smoothing model or the Permanent Income Hypothesis (PIH). That is, the tax rate used to finance UI is not forced to instantaneously adjust to balance the state government budget as is true for general fund expenditures, instead states can theoretically follow tax smoothing or consumption smoothing strategies.[2] An alternative possibility, however, is that state governments are impatient, and would want to spend the savings account immediately. Constraints on doing so include political opposition from raising taxes or cutting benefits during bad times, and the constraint imposed by the federal government on borrowing to fund UI trust fund shortfalls.

Our empirical work therefore uses a panel data set of the 50 U.S. states from 1976-2010 to model how state governments manage their UI trust fund savings accounts. We first test whether the time path of state UI taxes follows a Barro tax smoothing model, or are consistent with a Permanent Income Hypothesis (PIH) type of consumer, and find using unit root tests both by state and as a panel that neither describes the data well.[3] We then estimate a descriptive VAR model with UI taxes and benefits. The resulting impulse response functions do not suggest temporary behavior to smooth consumption. Instead, we find that innovations in tax levels do not persist over time, and further that benefit increases are followed by increases in taxation. While we find that benefit payment increases exhibit a temporary component, we also find a considerable permanent component as well.

[2]That is, most state general fund expenditures are required to follow an annual balanced budget, see Poterba (1994).

[3]These models employ different assumptions: in the PIH, income is exogenous and consumption is smoothed, and in the Barro model expenditure is exogenous and taxes are smoothed.

We estimate an ad hoc panel regression model to test how UI benefits and taxes respond to changes in trust fund balances. The estimation results suggest that state governments increase the generosity of UI benefits when trust fund savings balances are high. Increased UI expenditure is not the only path by which high savings balances are used, however, as we also find that state governments reduce UI taxes when savings balances are high. Finally, we find that when the state economy is strong UI benefits are increased, which of course also implies that benefits are reduced when the state economy is weak. This final result is the opposite of the nominal design of UI, where benefit expenditures are expected to increase in bad economic times. The results from the ad hoc model, however, are consistent with political UI managers that exhibit impatience by spending resources when they are available. On the other hand, the policy makers may also fear exhausting the UI trust fund balance in bad times, in which case the combination of these two influences suggests behavior consistent with the Carroll (1997) buffer stock model.

In a buffer stock model, an economic agent would maintain a precautionary savings account because of the fear of running out of money, or equivalently, of facing high costs from extreme policies to remedy a UI funding shortfall. If that same agent were impatient, defined as having an internal discount rate greater than the market rate of interest, then that agent would not allow the savings account to become too large. Jappelli, Padula, and Pistaferri (2008) have examined a buffer stock model using individual behavior, but find very little support using individual level data. We simulate their buffer stock model using parameters estimated from our data on state UI programs. We compare two statistical outcomes, a covariance condition which compares how both consumption and savings varies with deviations from target savings, and the actual level of target savings. In stark constrast to the failure of the buffer stock model for explaining individual behavior, we find that the behavior of state governments in managing their UI program appears quite consistent with buffer stock savings behavior. The conclusion which emerges is that UI program managers must be forward looking, and have a degree of impatience which is relatively well balanced with their degree of risk aversion. We therefore believe the buffer stock model offers a useful starting point for modelling how politicians manage the stock of savings for sub-national governments.

3.2 The Unemployment Insurance System, and Data

The UI program consists of fifty individual programs, one per state, although within a federal government policy umbrella. States are allowed to vary both the eligibility rules, and benefit amounts, within certain parameters.[4] If a person has been working and loses their job due to "inadequate demand," that person may receive benefits from the state UI fund. Benefits are generally paid to equal about 60 percent of prior wages. States finance their UI program with an earmarked tax on employers. The tax rate varies between firms since it is partially experience rated, and it is typically only levied against the first $9,000 in annual wages.[5] In this way the tax is essentially a lump sum tax per employee. Recognizing that the share of the workforce that is unemployed is cyclical, states maintain a saving account, called a trust fund, for UI. The earmarked tax is paid into the UI trust fund while benefits are paid out of the UI trust fund. While in theory there is no interaction with the general fund of the state and thus no inter-play between various other taxes and expenditures, in fact there are a variety of taxes on firms. Thus state governments could raise or lower the level of UI taxation, and compensate with reverse changes of firm taxation

[4] http://www.ows.doleta.gov/unemploy/uifactsheet.asp is the US Labor Department website with facts about the program.

[5] The tax base varies between $7,000 and $16,000 in annual wages.

in the General Fund, and thus move money from the UI trust fund to the general fund or vice versa.

States' unemployment taxes are deposited with the US Treasury and states' UI systems are able to borrow from the Treasury if their UI Trust Fund account goes to zero. The federal government pays interest on savings and charges state governments interest on loans; additionally there is a requirement for lending that state UI systems must be fundamentally solvent as determined by the Department of Labor (DOL).[6] Thus, the primary impediment to state borrowing is in the form of the implicit regulation by the DOL. This suggests that the shadow price on borrowing for states could be extremely high and indeed, state borrowing from the Treasury is limited—this is important because a crucial feature of the buffer-stock model is that agents are unable to borrow beyond a fixed limit.[7] Our data suggests that no state goes beyond borrowing 5% of its covered wages.

Table 3.1 presents the means of the panel data we use to examine state government management. Our panel of the 48 mainland U.S. states is from 1976-2008. The start date is dictated by the absence of state specific unemployment rates before 1976, although experimentation with other parts of the model suggest this restriction is not central to the results. The Unemployment Insurance program information is available from the DOL as all of the states run their UI program under the federal policy umbrella. The federal portion dictates that states have a similar framework of their tax and benefit structures, although they are free to make significant policy choices on the margin that cause significant policy differences between states (Craig and Palumbo, 1989). Also important is that the federal policy creates the UI Trust Fund for each state. The trust fund balances we use are reported

[6]In the environment of 2010-11 Congress has passed a waiver on interest payment on loans for all states.

[7]While the law does not set a fixed limit on borrowing by the UI systems, neither is there a fixed limit on how much consumers can borrow, and in our view the borrowing constraint is at least as important for state UI systems as it is for consumers.

as of the first of the year.

All of the dollar data in our project is deflated by the CPI. For the UI tax and benefit data, we normalize by covered wages, reflecting the insurance aspect of UI. UI does not necessarily cover all wages earned in the economy, as self employed workers are not generally covered (unless incorporated), and there are often caps on the total wages covered by UI (since benefits are a function of covered wages). Nonetheless, covered wages are over 90 percent of total wages.

The means of our data are presented in Table 3.1. It shows that the UI program benefits and taxes are just under 1% of covered wages on average, although the share clearly fluctuates during business cycles. It also shows that the trust fund balance averages about 16 months of covered wages, so is substantial, although not large enough to forego taxation altogether for long. Interest earned by the trust fund averages 8% of the initial year balance for states. At the same time, about 12% of states are in debt to the federal government at any point in time. For those in debt, the debt levels are slightly above the average years' reserves, so debt is important but is clearly not the modal behavior by states. Table 3.2 presents the dollars per capita of the variables in Table 3.1.

Craig and Palumbo (1989) address the motives underlying UI, and find that eligibility varies substantially between states, and to a lesser extent so do benefits conditional on earned wages. They show that the variability is consistent with explicit policy choices by state governments, and in fact explain part of these UI choices using welfare policy choices. We therefore build our model to incorporate the "core" unemployment payments compared to the discretionary payments. Our definition of core payments is meant to include payments to UI recipients that would be eligible at all points in time. Discretionary payments are therefore those that states choose to make, or choose not to make, to people who are only eligible for UI in some circumstances at some points of time, but not other times. Examples would be UI payments to part-time workers, to workers with very short total work histories, to workers with a less well defined reason for separating from the employer, or to workers laid-off from a job after a very short period of work. Specifically, we run a regression on aggregate benefits as a function of the unemployment rate, and we use the results of this regression to construct the expected value as our estimate of these 'core' payments.[8] We perform a similar procedure for UI taxes, in that a portion of UI taxes go to fund the 'core' UI payments, and the remainder is used to fund the discretionary UI payments.[9]

3.3 Model, Test, and Specification of Government Behavior

The simplest model of forward looking government behavior is the Barro (1979) tax-smoothing model: a government facing an exogenous stream of expenditures and an increasing convex cost of period-by-period tax collection, will under certainty keep a constant tax rate such that the present value of taxes covers the present value of expenditure. Under uncertainty and quadratic costs, the government will display "certainty equivalence" and choose the period t tax rate such that, if kept unchanged, it would have the same present value as the expected present value of expenditure. Barro showed that a simple testable implication is that the tax rate is a martingale (typically, if imprecisely, referred to as a random walk). Similarly, if utility of benefits are well approximated by a quadratic utility function and the discount rate is similar to the interest rate, expenditures will follow Hall (1978)'s celebrated version of the Permanent Income Hypothesis (PIH) and be well modeled as a martingale process. If tax rates are martingales, an autoregressive model fitted

[8]Specifically, we run a regression for each state to get a state-specific estimate of how UI beneifts vary with the unemployment rate, and then average the estimates.

[9]The notes to Table 3.8 report these regressions.

to tax rates should display a unit root. We therefore start out testing whether tax rates are approximately martingale by performing unit root tests. We also examine if expenditure rates are well fitted by autoregressive time series models with unit roots. If so, tax smoothing cannot be identified from unit roots, as pay-as-you-go behavior would deliver unit roots in tax rates for the simple reason that expenditures display unit roots. We next estimate a Vector AutoRegressive (VAR) model for expenditures and taxes and illustrate the intertemporal patterns in taxes and benefits, using both "rates" normalized by covered wages and by using Impulse Response Functions (IRF), although we do not interpret the error terms as structual innovations.[10] The VAR model is a reduced form model without structural interpretation, but it allows us to observe the adjustment pattern for both taxes and expenditures over time (Craig and Hoang, 2011).

There are good reasons to believe that governments may not act to perfectly smooth economic fluctuations. One reason is that politicians are under pressure to deliver cost effective services to their current taxpayers, so they are likely to reduce UI taxes to allow them room to increase other firm taxes, and generate a current service stream rather than build a UI trust fund. Similarly, if general fund revenues are low and there is political resistance to tax increases, a state government potentially may reap a political benefit from increases in UI benefits paid out, even if the UI trust fund is reduced. Thus the segmentation of the UI program from state fiscal policy in other policy dimensions is a political choice, rather than an institutional necessity. Further, there are other public good problems besides "smoothing," and thus it may not be a surprise that several papers have rejected the PIH model for state governments and include a "rule of thumb" non-forward looking aspect (see, e.g., Dahlberg, Matz, and Tomas Lindstrom 1998), although this involves an unsatisfactory

[10] Our preferred specification normalizes both taxes and expenditures by covered wages, although we show our conclusion is not sensitive to the normalization specification.

deviation from optimizing behavior.

The unit root tests we conduct, as well as the estimates of the VAR, strongly rejects these perfect foresight specifications. We therefore estimate a broader more explorative specification and, to preview, find evidence that states become more generous with benefits when the UI trust fund balance is high (although by implication this means benefits are less generous when the trust fund balance is low). We find equivalent behavior with taxation, that is that taxation tends to fall when the UI trust fund is flush, and tends to increase when it is low. Such a pattern is consistent with impatience (politicians with discount rates higher than interest rates would like to spend the saving in the trust fund). This view would be overly simplistic, however, because in general states do not exhaust their trust fund in its entirety, implying that politicians are forward looking to some extent, and so anticipate the loss of utility in future periods if the ability to pay UI benefits is exhausted. Despite these behaivoral justifications, the implication of this pattern of procyclical benefits and counter-cyclical taxation is the opposite of the usual automatic stabilizer label that is given to the UI program.

Models of impatient consumers that have an aversion to exhausting their savings have been popularized by Carroll (1997) and Deaton (1991). A large of number of papers have attempted to test a key implication of the model: that "buffer stock" savings are larger when uncertainty is larger. The only direct test of buffer stock savings behavior, however, is a recent paper by Japelli, Pistaferri, and Padula (2008) that directly examines if consumers are prone to spend more if their savings exceed their (self-reported) desired stock of savings. We interpret (the discretionary part of) UI benefits as providing utility to politicians.[11] To our knowledge, we provide the first empirical evidence of buffer stock savings behavior by

[11] Likely due to higher benefit leading to higher chance of reelection, but we do not model the deeper meaning of politicians' "utility" in this paper.

any agents, and believe our demonstration of buffer stock behavior by governments may hold important insights into policy designs that potentially aim at using governments to smooth economic fluctuations.[12]

3.4 Buffer Stock Model

Our empirical approach is to follow the approach of Japelli, Pistaferri, and Padula (2008) (JPP) to determine whether state governments exhibit the Carrol (1997) buffer stock behavior when managing their UI savings accounts. The JPP approach is unusual, because they directly focus on the desired level of saving—i.e., the buffer stock. Our approach is similar, except that unlike their data our state government data does not contain a self reported desired buffer stock. Thus our objective is to use the JPP methodology to simulate the Carroll (1997) model, but then compare the resulting level of buffer stock savings to the level that is actually in our data. To construct the simulation problem, we develop the analog to individual consumption and income using our state UI data. The key factors in the model are the degree of risk aversion which tends to support a level of savings, and the rate of time discounting which tends to reduce the level of savings.

For our state government UI analog to the buffer-stock model, assume politicians get utility from the level of benefits paid, which we will model as consumption, C. Then the utility function can take the form of a state agent (consumer) maximizing:

$$\Sigma_{t=1}^{\infty}\beta^t \frac{1}{1+\rho} C_t^{1-\rho}$$

where β is the time discount factor, C_t is consumption, and $\rho > 0$ is the coefficient of

[12] Part of this claim is because Japelli, Pistaferri, and Padula (2008) find no buffer stock behavior in the individual data they use for their simulation.

relative risk aversion. The dynamic budget constraint facing the state government agent is

$$W_{t+1} = R\,(W_t - C_t + Y_t)$$

where R is an interest rate factor assumed constant over time, W_t is non-human wealth which in our model is the trust fund savings account, and Y_t is labor income (i.e., income apart from interest income), which for us will be covered wages. In the original model agents are credit constrained and not allowed to borrow; i.e., $W_t > 0$, while in our work we set a limit to possible borrowing. The funds available for consumption at the beginning of period t are $W_t + Y_t$ which Carroll (1997) denotes "cash-on-hand." For our UI model, income is tax receipts, so cash-on-hand equals the total of the trust fund at the beginning of the fiscal year plus tax receipts for the year.

Income is assumed exogenous and is typically modeled as the sum of a persistent (random walk) component, labeled permanent income, and a temporary (white noise shock) component:

$$Y_t = P_t\,V_t\ , \tag{3.1}$$

$$P_t = G\,P_t\,N_t\ . \tag{3.2}$$

P_t is the permanent (unit root) component of income with log-normally distributed innovation N_t, where $\mathrm{Var}(\ln(N_t)) = \sigma_N$ and $E(\ln(N_t)) = 0$. V_t is the transitory (white noise) component of income which is log-normally distributed with $\mathrm{Var}(\ln(N_t)) = \sigma_V$ and $E(\ln(V_t)) = 0$.[13] G is the deterministic growth rate of income.

Crucial features of the model are the lower bound on wealth (a maximum to borrowing) and a discount factor β which is lower than the interest rate factor. Impatience implies that the government desires to consume up-front and not build up savings, because the discount

[13] P_t is sometimes referred to as permanent income, although in the context of the PIH model, permanent income shocks would be $\Delta P_t + (R-1)N_t$.

rate is greater than the interest rate. Conversely, however, because zero consumption implies very high (infinite) dis-utility, the government will hedge against very low consumption by building a "buffer-stock" of saving, called here the UI trust fund, to avoid running out of funds. Agents adjust their consumption and their target wealth one-to-one with movements in permanent income. We define all of the dollar variables (consumption, income, and cash on hand) relative to permanent income, and the normalized variables are all stationary. The model is solved by specifying a parameter for risk aversion, a personal discount factor, and an interest rate (Carroll, 1997, JPP, 2008).

The "target buffer stock" is denoted x^*, which is more precisely the target ratio of cash-on-hand relative to permanent income. The innovation in Japelli, Padula, and Pistaferri (2008) is that they are able to directly make use of consumers' (desired) buffer stock and examine if consumers whose "cash-on-hand" (savings plus current income) exceeds the buffer stock tend to increase consumption, thereby reducing deviation between cash-on-hand and the desired buffer stock of savings. Japelli, Padula, and Pistaferri (2008) test the model on their data based on the observation that agents whose cash-on-hand (relative to permanent income) exceeds the target will tend to decrease cash-on-hand in order to move toward the target. More precisely, they argue that the covariance of the cash-on-hand to target gap is negatively correlated with expected changes in cash at hand:

$$\mathrm{Cov}\{x_t - x^*, E_t(x_{t+1} - x_t)\} < 0 \ .$$

Using the structure of the model, JPP rewrite this in terms of observable variables as

$$\theta = \frac{\mathrm{Cov}\{x_t - x^*, c_t\}}{\mathrm{Cov}\{x_t - x^*, x_t\}} \ . \tag{3.3}$$

We follow JPP and estimate the covariance ratio θ from our data and test if the buffer-stock model provides a reasonable fit to the data by comparing the empirically estimated value to the value of θ implied by the model.

The covariance ratio satisfies a theoretical constraint (larger than $1 - G/(Re^{\sigma_N^2})$) but in order to find exact numerical values for θ as a function of preference and income parameters, one needs to simulate the model. We do so below for a range of values of the risk aversion parameter and the discount rate.

3.4.1 Mapping the UI Administrators' Decision Problem into the Consumer Model

We assume that the politicians who decide on the taxes and benefits derive utility from setting a high level of benefits. This utility would be likely derived from generous benefits increasing the consumption of voters who then might be more likely to vote for the incumbent politicians. We do not attempt to sort out this mechanism but assume that higher benefits deliver utility to politicians. However, part of benefits are clearly mandated by law to insure unemployed and we choose to consider the discretionary part of benefits as the equivalent of consumption in the buffer stock model.

We define a time period as two years but will also show some results for one-year and three-year periods. The reason for choosing this interval is that governments—apart from rare exceptions—only change rules when a new budget is determined. This means that governments often can not react within a single year. Complicating matters, many states have two-year budgets. We do not have enough degrees of freedom to model states with different budgetary structures separately so we choose the two-year period as the best overall approximation. Regressions are done using non-overlapping two-year periods because it is hard to properly adjust standard errors for the serial dependence one would generate by using overlapping data.

We determine non-discretionary benefits by regressing UI benefits on the state unemployment rates. Residuals from this regression are assumed to be discretionary and we call these payments consumption.[14] That is, we regress benefits on unemployment for each state and find the average coefficient β. We then define non-discretionary benefits $C_{it} = \beta * (U_{it} - \overline{U}_{i.})$, where U_{it} is unemployment in state i in period t and $\overline{U}_{i.}$ is average unemployment in state i. *In the next iteration of this paper, we will add discretionary taxes, with a negative sign, to consumption.* More precisely, we perform the regression of benefit divided by covered wages (a unit free number) on unemployment and multiply the right hand side by covered wages when generating C.

We define income as unemployment taxes minus non-discretionary benefits paid. *In the next iteration of the paper, we will use the non-discretionary part of taxes instead of total taxes. We will approximate the non-discretionary part of tax with the fitted value from a regression of taxes on lags of non-discretionary benefits and covered wages.* We define permanent income as the three period moving average of income. In our preferred specification, using two-year periods, our moving average spans six years. As in the model, all variables are normalized by permanent income before we estimate the covariance ratio which is our (and JPP's) main test of buffer-stock behavior.

Cash-on-hand is defined as the trust fund balance at the beginning of the period plus income as we define it plus 0.05*Covered Wages. This last term is added to allow for the possibility that state government UI funds may borrow from the federal government. There is a significant administrative shadow price of doing so, however, and the maximum we ever observe a state to borrow is slightly below 5% of the covered wages. We specify target cash-on-hand as the three period moving average of cash-on-hand spanning six years.

[14] Craig and Palumbo (1998) show that UI benefits are heterogeneous by state due to state government preferences over equity.

Compared to the implementation of JPP, our data has the advantage of delivering exact savings balances, of having infinitely lived agents which implies that we do not have to separate buffer stocks from life-cycle savings, and of having precisely (albeit approximated) income where individual agents rarely report sources of "income" such as capital gains (the model assume lending at a constant interest rate), inheritance etc. JPP's data directly measures consumption rather than our using a utility index on discretionary policy and they have access to self-reported target wealth observations.

This covariance ratio satisfies a theoretical constraint (larger than $(1 - G/(Re^{\sigma_N^2})$ but in order to find exact numerical values for θ as a function of preference and income parameters, one needs to simulate the model. Because governments generally adjust finances slowly, we define each "period" for our model as two years. This means we aggregate the data for each two year period and treat it as a single observation. We do not overlap the data, each period is consecutive (we do not use overlapping data because this usually leads to underestimated standard errors in regressions).

The definition of our variables to fit the JPP model starts with income. We define income as unemployment taxes minus non-discretionary benefits paid, where we determine non-discretionary benefits by regressing UI benefits on the state unemployment rates. Residuals from this regression are therefore assumed to be discretionary, and we call these payments consumption. That is, we regress benefits on unemployment for each state and find the average coefficient β. We then define non-discretionary benefits as $\beta * (U_{it} - \overline{U}_{i.})$, where U_{it} is unemployment in state i in period t and $\overline{U}_{i.}$ is average unemployment in state i. Cash-on-hand is defined as the trust fund balance at the beginning of the period plus income minus consumption + 0.05*Covered Wages. This last term is added to allow for the possibility that state government UI funds may borrow from the federal government. There is a significant administrative shadow price of doing so, however, and the maximum we ever observe a state to borrow is slightly below 5% of the covered wages. We define permanent income as the three period moving average of income, which because each period is two years our moving average spans six years. Similarly, we specify target cash-on-hand as the three period moving average of cash-on-hand spanning six years.

3.5 Results

Our results proceed in three steps. We first estimate a descriptive VAR with six lags to explore the relevance of the PIH or Barro tax smoothing models, and to provide descriptive statistics. These models are rather decisively rejected by the data. We then estimate an ad-hoc panel data model, in which we specify how either UI taxes or UI benefits paid respond to the level of the UI trust fund. We find that taxes generally fall as the trust fund balance grows, and that UI benefits grow as the trust fund balance grows. Both of these actions suggests buffer stock behavior, so our last step is to simulate Carroll's (1997) model. The simulation gives us a target buffer stock savings level, which we find is close to the actual average levels in our data. Further, the simulation shows strong consistency with the covariance ratio condition derived in JPP, in which increases in the trust fund relative to the target is compared to increases in the trust fund relative to UI benefits. We find our data is also quite consistent with the covariance ratio condition.

3.5.1 VAR Regression Results

We explore the dynamic relation between UI taxes and benefits by estimating a VAR model with six lags of both UI taxes and benefits. We do not consider this a structural estimation because driving variables, such as wages and unemployment, are left out; however, VARs depict the dynamic relations between our two main variables succinctly. Moreover, one can directly get an impression of the validity of benchmark models such as the PIH and the Barro tax-smoothing model. In the PIH model, for example, consumption (UI benefits) reacts instantly, not gradually, to changes in income (UI taxes). For the Barro tax-smoothing model, UI taxes react instantly to spending (UI benefits) shocks rather than gradually. In both cases, these reactions are because the shock communicates new information, which we expect the economic agent to instanteously use to adjust to the new permanent path. The other implication, of course, is that temporary shocks should cause little change.[15]

In Table 3.3 we report results of Dickey-Fuller unit root tests for log taxes and log benefits. UI benefits will be martingales, not rejecting unit roots, if benefits can be described as a consumption good for politicians with quadratic utility functions (see Hall, 1978 for more details). While unit roots tests are not very powerful for annual samples of only 38 years, we reject a unit root in benefits in 24 of 48 states at the 10 percent level of significance. Similarly for the Barro model, the unit root for taxes is rejected for only 12 states when each is tested separately.

Although these tests have low power, they suggest that 3/4 of the states potentially are following a tax smoothing path. Our interpretation, however, is that states engage in some tax smoothing, but not to the extent of following the Barro model closely.[16] Pooled panel unit root tests, reported in the second row of Table 3.3, reject a unit root for UI taxes as well as benefits. The statistical rejection is slightly stronger for benefits than it is for taxes, but taxes are clearly not being systematically smoothed.

The coefficients from estimating the VAR are reported in Table 3.4 but the results

[15]See Aiyagari, Marcet, Sargent, and Seppala (2002) for a more recent treatment, that nonetheless suggests these interpretations hold, expecially in an environment where the government has a borrowing constraint as appears true for UI.

[16]State-level output and income are themselves unit root processes, see for example Asdrubali et al. (1996).

are maybe more easily read from the graph of the Impulse Response Functions (IRFs) shown in Figure 3.1. Consider the regression of taxes on lagged benefits and taxes. Lagged benefits are significant with large coefficients of 0.20-0.30 for lags 1–4 clearly contradicting the Barro tax-smoothing model which implies that taxes are martingales for which all lags would be insignificant. Overall, taxes appears to adjust to benefits changes, likely in order to maintain a positive trust-fund balance. *This endogenous aspect of taxes is ignored in the present implementation of the buffer-stock model below.* Lagged taxes enters with negative coefficients indicating that UI-systems have something like a target for tax rates.[17]

For the PIH model to explain how state governments manage their UI savings, we would expect that UI Benefits would be a martingale. In contrast, however, the results in Table 3.4 show that lagged benefits are very significant at explaining current benefits, indicating gradual adjustment to shocks. Conversely, the coefficient results of Table 3.4 do not show a consistent pattern of lagged taxes affecting current benefits. Several of the coefficients are insiginficant, and the signs switch for those that are significant. While not a formal model, and noting that there are no control variables, the general indication is that taxes are not adjusted by policy makers to provide benefits. The first lag of benefits indicates serial correlation in unemployment, but mean reversion takes is quite slow, at least 3 to 4 years (the standard error band is likely much too narrow for longer lags in the figure because they do not take into account the arbitrariness involves in selecting the correct number of lags).

[17]This hypothesis may be rejected because the design of the UI program is that benefits should be paid out counter-cyclically rather than at politicians' discretion. The test for unit roots in benefits is not only a test of the PIH, it is also important for the interpretation of the test of taxes. That is, if it is found that benefits follow a unit root, the test for UI taxes becomes uninformative since tax smoothing cannot be separated from simply budget balance. On the other hand, if the tests reject that UI benefits follow a unit root, then it is possible that our tests for UI taxes can differentiate whether taxes are designed by state governments to be smoothing taxes—i.e. whether UI taxes follow a unit root consistent with a smoothing governmental objective.

3.5.2 Buffer Stock Regressions and Simulations

In this section we present two analyses. One is the ad hoc regression that estimates how UI benefits or taxes react to changes in the level of trust fund savings. Motivated by the results of this test, we then explore whether buffer stock behavior might explain state political UI choices. Specifically, we adapt our data to the JPP (2008) model of consumption and income, and compare the simulation using parameters estimated from our data to the UI data, and find that the buffer stock model seems to be a good fit.

Table 3.5 presents the results of an ad hoc regression, in which we separately model UI benefits or taxes as a function of, among other things, the level of the UI trust fund. Benefits are unsurprisingly found to react strongly to unemployment, and as well to the business cycle as captured by output growth. A recession dummy further captures the need for benefits in recessions. Benefits are found to rise with the level of GDP, which could include that politicians in wealthier states are more generous with unemployment benefits on average, or that benefits to the "marginally unemployed" rise during periods of high GDP. Interestingly, benefits are found to have a positive and highly significant response to changes in the trust fund balance, a finding consistent with impatience. The tax equation finds that UI taxes rise in recessions, which might be surprising if we think about UI as an automatic stabilizer, and not so surprising if states are reacting to larger than usual UI expenditures. The regression further shows that taxes are raised when the trust fund balance is low, even after controlling for the state of the economy. While there is not an explicit model motivating this regression, the results are consistent with state government UI officials acting as buffer stock agents. That is, when funds are plentiful and the trust fund balance is high, politicians desire to spend money, including on UI benefits. On the other hand, when the business cycle is negative and the trust fund begins to run down, we find state policy makers respond to restore the trust fund, even if it means raising taxes during bad times. To formally test the buffer stock idea, we use the JPP (2008) simulation of the Carroll (1997) model with our UI data.

The simulation results of the buffer stock model are shown in Table 3.6. The parameters we use in the simulation are derived from our panel data, where we treat UI benefits as consumption and UI taxes as income. The simulation is for 50 states with discount rates as indicated by β, and coefficients of risk aversion as indicated by ρ. The variance in transitory income is indicated by σ_V, as calculated from our data. The objective is to find the resulting values of θ, which is the covariance ratio as indicated in equation (3.3). This ratio illustrates how the deviation from target wealth correlates with consumption, divided by the correlation between deviations from target wealth and the level of target wealth. We also use the simulation results to find the resulting value of x*, which is the target cash-on-hand to permanent income ratio. According to JPP, covariance ratios between about .4 and .8 are consistent with buffer stock behavior, since it is consistent with extra consumption being correlated with buffer stock levels. The simulation results in Table 3.6 show that virtually all of the resulting covariance ratios, θ, are within this range for a wide variety of parameterizations. When the results in Table 3.6 are compared to the actual data in Table 3.8 for the x* (target wealth, given here as the trust fund balance divided by covered wages), we see that the x* values generally fall within the range indicated by the data. We conclude from this that the buffer behavior implied by the buffer stock model is quite consistent with actual state government management of their UI systems.

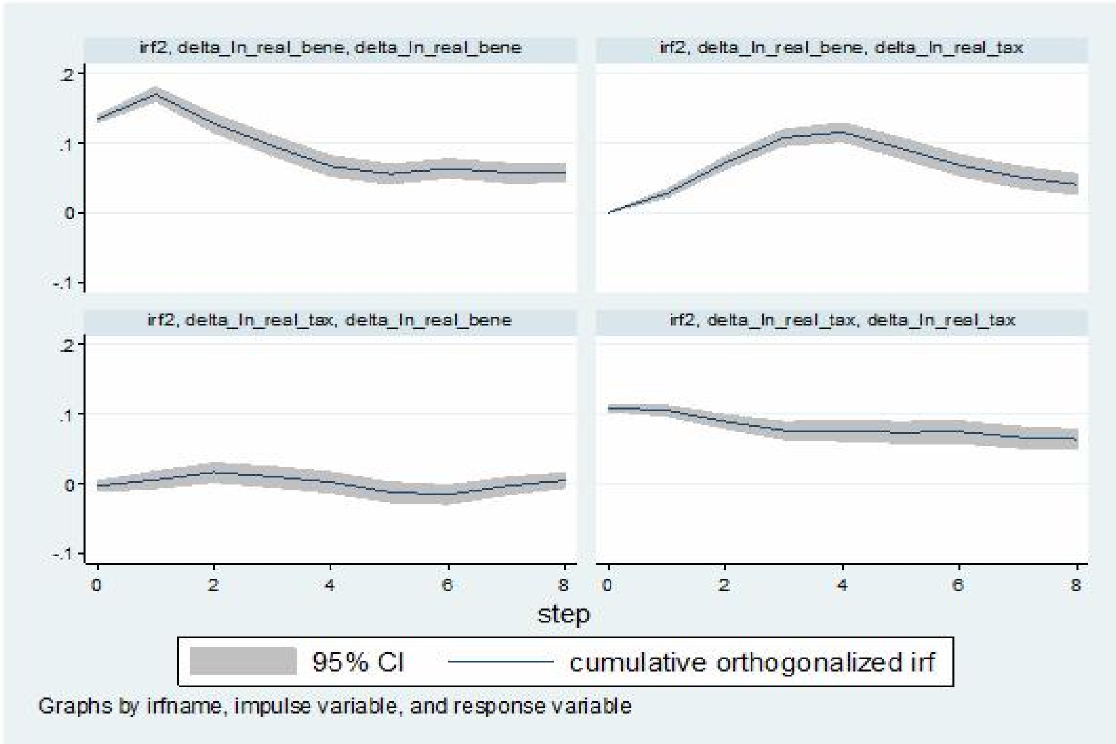
3.6 Summary and Conclusion

The objective of this paper has been to examine how state governments manage the savings accounts that they accumulate to finance unemployment benefits. We believe this is the perfect institutional arrangement to examine government behavior with respect to savings, especially in the face of business cycle movements. The public good justification for state intervention seems well justified, thus private individual or firm actions are unlikely to obscure the objectives of state government officials. Further, UI is clearly the institution that is designed to respond to economic fluctuations.

We find that state government officials apparently are forward looking, but not to the extent that they would follow Barro's advice to smooth taxes over time. Instead, we find that state governments alter both UI taxes and UI benefits in a manner that is consistent with impatient actors, but also actors that are risk averse. Indeed, we find using our simulations that state government behavior can be well characterized by a buffer stock model, suggesting relatively small fluctuations in the stock of savings around a target level.

One implication of our work is that at least in the case of UI, governments seem to be more forward looking and less impatient than the individuals in JPP's data set, which might be inconsistent with the popular notion that government agents are "too present oriented." The question which we have not yet addressed, but which would be crucial for understanding whether the UI institutional model could be extended more broadly to overall government expenditure, is the relative importance of specific institutional features for our behavioral findings. One implication of our findings, however, is that there is little government behavior that is "automatic," as in automatic stabilizers, rather governments continually make choices and these choices depend on the objectives and tastes of policy makers, captured here by the trade-off between impatience and risk aversion.

Figure 3.1: Impulse Response Functions of Benefits and Taxes



Notes: Figure 3.1 displays the estimated impulse responses following a one standard deviation shock to benefits (upper panels) or taxes (lower panels).

Table 3.1: Summary Statistics

		State governments (1976 – 2008)
Benefits (percent)	Mean	0.92
(UI payments/covered wages)	std1	0.31
	std2	0.37
Taxes (percent)	Mean	0.90
(UI taxes/covered wages)	std1	0.31
	std2	0.35
Trust fund balance (percent)	Mean	1.23
(UI TFB/covered wages)	std1	0.75
	std2	1.05
Federal loan balance (percent)	Mean	0.17
(Federal loan balance/covered wages)	std1	0.26
	std2	0.53
Federal loan balance (Conditional on $\gg 0$)(percent)	Mean	1.39
(Federal loan balance/covered wages)	std1	0.84
	std2	0.77
Interest credited to trust fund (percent)	Mean	0.10
(Interest/covered wages)	std1	0.05
	std2	0.06
GSP (ratio)	Mean	2.97
(GSP/covered wages)	std1	0.34
	std2	0.15
Unemployment rate (percent)	Mean	5.79
	std1	1.06
	std2	1.65
Observations		1,584

Notes. "std1" (cross-section): time average of $\left[(1/n)\sum_i (X_{it} - \bar{X}_t)^2\right]^{1/2}$ where $\bar{X}_t$ is the period t average of X_{it} across states, and n is the number of states. "std2" (time-series): average over i of $\left[(1/T)\sum_t (X_{it} - \bar{X}_i)^2\right]^{1/2}$ where $\bar{X}_i$ is the time average of X_{it} for state i, and T is the number of years in the sample. Benefits, Taxes, Trust fund balance, GSP, Federal loan balance, Interest credited to trust fund are all normalized by Covered wages. Federal loan balance is positive for 12 percent of observations.

Table 3.2: Summary Statistics (Real Dollars Per Capita With Base (1982-1984))

		State governments (1976 – 2008)
Benefits	Mean	52.19
	std1	21.21
	std2	16.79
Taxes	Mean	51.16
	std1	21.51
	std2	15.33
Trust fund balance	Mean	71.28
	std1	39.85
	std2	62.40
GSP	Mean	17,153
	std1	2,733
	std2	2,570
Federal loan balance	Mean	9.13
	std1	14.69
	std2	28.26
Federal loan balance (Conditional on $\gg 0$)	Mean	75.29
	std1	44.66
	std2	38.85
Interest credited to trust fund	Mean	5.80
	std1	2.68
	std2	3.72
Population	Mean	5,320,566
	std1	5,613,499
	std2	1,022,987
Observations		1,584

Notes. "std1" (cross-section): time average of $\left[(1/n)\sum_i (X_{it} - \bar{X}_t)^2\right]^{1/2}$ where $\bar{X}_t$ is the period t average of X_{it} across states, and n is the number of states. "std2" (time-series): average over i of $\left[(1/T)\sum_t (X_{it} - \bar{X}_i)^2\right]^{1/2}$ where $\bar{X}_i$ is the time average of X_{it} for state i, and T is the number of years in the sample. Benefits, Taxes, Trust fund balance, GSP, Federal loan balance, Interest credited to trust fund are all expressed in real per capita terms. Federal loan balance is positive for 12 percent of observations.

Table 3.3: AR(1) Estimation

	log(tax/covered wages)	log(benefits/covered wages)
State by state Unit Root Tests		
Number of rejections:	12	24
Panel AR(1) estimation	0.94***	0.87***
	(0.01)	(0.01)
Panel Unit Root test	–0.07	–0.12
	(-7.05)	(–8.52)
R-squared	0.88	0.77
N. of obs	1536	1536

Notes. The first row reports number of rejections of unit roots in augmented Dickey-Fuller tests. The second row reports the point estimates of the respective lagged variable in a standard panel AR(1) estimation with state fixed effects with standard errors in parenthesis. The last rows report test statistics and p-values from panel unit-root tests. *, ** and *** refer to the 10%, 5% and 1% significance level respectively

Table 3.4: VAR Estimation

	Δ(**Taxes**)	Δ(**Benefits**)
lagged Δ(Taxes) :		
$(t-1)$	-0.03	0.09*
	(0.03)	(0.04)
$(t-2)$	-0.16***	0.07
	(0.03)	(0.03)
$(t-3)$	-0.16***	-0.04
	(0.03)	(0.03)
$(t-4)$	-0.07**	-0.00
	(0.03)	(0.03)
$(t-5)$	-0.07**	-0.10**
	(0.03)	(0.03)
$(t-6)$	0.01	-0.00
	(0.03)	(0.03)
$(t-7)$	-0.04	0.04
	(0.02)	(0.03)
lagged Δ(Benefits) :		
$(t-1)$	0.21***	0.27***
	(0.02)	(0.03)
$(t-2)$	0.27***	-0.41***
	(0.02)	(0.03)
$(t-3)$	0.30***	-0.08**
	(0.02)	(0.03)
$(t-4)$	0.20***	-0.31***
	(0.02)	(0.03)
$(t-5)$	0.09***	-0.07*
	(0.02)	(0.03)
$(t-6)$	0.09***	-0.06*
	(0.02)	(0.03)
$(t-7)$	0.02	-0.13***
	(0.02)	(0.03)
N. of obs	1175	1175

Notes: The table reports a VAR estimation for 1976-2008 period using the equation:

$$\begin{bmatrix} \Delta(\ln(Taxes/CoveredWages)_{it} \\ \Delta(\ln(Benefits/CoveredWages)_{it} \end{bmatrix} = \sum_{k=1}^{7} \begin{bmatrix} a_k & b_k \\ c_k & d_k \end{bmatrix} \begin{bmatrix} \Delta(\ln(Taxes/CoveredWages)_{it-k} \\ \Delta(\ln(Benefits/CoveredWages)_{it-k} \end{bmatrix}$$

Std. err. in parentheses. ***, **, * significant at the 1%, 5% and 10% levels respectively.

Table 3.5: Ad hoc Regressions of Benefits and Taxes

	Benefits Coef./Std. err.	Taxes Coef./Std. err.
urates	0.03***	0.01
	(0.01)	(0.01)
log(GSP/Pop)	0.26**	0.16
	(0.08)	(0.09)
Δ log(GSP/Pop)	-2.57***	-0.19
	(0.27)	(0.22)
log(trust fund bal at t-1)	0.47***	-0.80***
	(0.10)	(0.12)
Δ (log Trust fund bal)	-0.28	-0.76*
	(0.19)	(0.35)
Recession dummy	0.02*	0.04**
	(0.01)	(0.02)
lagged Benefits	0.68***	
	(0.03)	
lagged Taxes		0.80***
		(0.02)
R-squared	0.95	0.93
N. of obs	1536	1536

Notes: *, ** and *** refer to the 10%, 5% and 1% significance level respectively.

Table 3.6: The Simulated Covariance Ratio and Target Wealth

	σ_V=**0.1**		σ_V=**0.3**		σ_V=**0.5**	
	β=**0.9**	β=**0.94**	β=**0.9**	β=**0.94**	β=**0.9**	β=**0.94**
ρ=**0.5**	$\theta = 0.86$	θ=0.53	θ=0.69	θ=0.36	θ=0.54	θ=0.24
	x^*=1.10	x^*=1.32	x^*=1.13	x^*=1.56	x^*=1.26	x^*=1.97
ρ=**0.8**	$\theta = 0.75$	θ=0.27	θ=0.57	θ=0.21	θ=0.43	θ=0.17
	x^*=1.15	x^*=1.72	x^*=1.26	x^*=2.03	x^*=1.45	x^*=2.61
ρ=**1**	$\theta = 0.66$	*NA*	θ=0.49	*NA*	θ=0.38	*NA*
	x^*=1.24		x^*=1.37		x^*=1.61	
ρ=**1.4**	$\theta = 0.43$	*NA*	θ=0.35	*NA*	θ=0.26	*NA*
	x^*=1.51		x^*=1.69		x^*=2.04	

Notes: The table reports the median simulated covariance ratio θ and the median simulated target wealth to permanent income ratio x^* under alternative parameterization of a buffer stock economy populated by *50* individuals with same discount factor β living for *100* periods. ρ and σ_V stand, respectively, for the coefficient of relative risk aversion and the standard deviation of transitory income shocks. Simulations correspond to a standard deviation of permanent income shocks σ_N *=0.3* and a probability of zero income p *=0.01*. *NA* is reported in the cases where a fixed point solution does not exist (Carroll, 1997).

Table 3.7: IV Regression of Discretionary Benefits on Cash-on-Hand

	Benefits/ Covered wages
Diff=1	
Estimated coefficient of cash-on-hand	0.40*
	(0.22)
Observations	1392
Diff=2	
Start year=1977	
Estimated coefficient of cash-on-hand	0.49***
	(0.12)
Observations	672
Diff=3	
Start year=1978	
Estimated coefficient of cash-on-hand	0.45***
	(0.06)
Observations	384
State and year fixed effects	Yes

Notes: Standard errors in parentheses. For Diff=1 we treat each year as a period. For Diff=2 we treat two consecutive years to be a period. We sum taxes, benefits, covered wages, interest credited to the trust fund for two consecutive years be the value for a single period. For Diff=3 we treat three consecutive years to be a single period. We run an IV regression of discretionary benefits defined as [Benefits-β*(unemp-meanunemp)*covered wages] on cash-at-hand defined as [Trust fund balance+ .01 + taxes-β*(unemp-meanunemp)*covered wages]. We use the deviation between cash-on-hand and the target ratio of cash-at-hand as the instrument. We approximate the target cash-on-hand to be a 5 year moving average of cash-on- hand for Diff=1. We approximate the target cash-on-hand to be a 3 period moving average of cash-at-hand for Diff=2 and Diff=3 (i.e.; for Diff=2 we use the moving average of 3 periods of the 2 year sums). β is the between state mean of β generated from a state panel regression of benefits/covered wages on unemp. All variables are normalised by permanent income. Income is defined as [Taxes-β*(unemp-meanunemp)*coveredwages]. We define permanent income to be a 5 year moving average of income for Diff=1. For Diff=2 and Diff=3 we define permanent income to be a 3 period moving average of income. For Diff=2 the estimated coefficient of cash-at-hand is 0.43 if start year=1976. For Diff=3 the estimated coefficients of cash-on-hand are 0.48 and 0.49 respectively for start years 1976 and 1977. *, **, *** Significant at the 10 percent, 5 percent, and 1-percent level, resp.

Table 3.8: Cash-on-hand, Income and Ratio of Cash-on-Hand to Permanent Income

Variable Name	mean	std1	std2
Diff=1 (One year period)			
Cash-on-hand (percent)	1.06	0.26	0.36
(Cash-on-hand/GSP)			
Income (percent)	0.31	0.12	0.11
(Income/GSP)			
Ratio	4.17	1.64	1.86
β	0.0019	0	0
Observations	1584		
Diff=2 (Two year periods)			
Start year=1977			
Cash-on-hand (percent)	0.85	0.16	0.17
(Cash-on-hand/GSP)			
Income (percent)	0.31	0.12	0.09
(Income/GSP)			
Ratio	3.26	1.02	0.91
β	0.0018	0	0
Observations	768		
Diff=3 (Three year periods)			
Start year=1978			
Cash-on-hand (percent)	0.77	0.14	0.12
(Cash-on-hand/GSP)			
Income (percent)	0.31	0.12	0.09
(Income/GSP)			
Ratio	2.86	0.82	0.62
β	0.0019	0	0
Observations	480		

Notes: "std1" (cross-section): time average of $\left[(1/n)\sum_i (X_{it} - \bar{X}_t)^2\right]^{1/2}$ where $\bar{X}_t$ is the period t average of X_{it} across states, and n is the number of states. "std2" (time-series): average over i of $\left[(1/T)\sum_t (X_{it} - \bar{X}_i)^2\right]^{1/2}$ where $\bar{X}_i$ is the time average of X_{it} for state i, and T is the number of years in the sample. Diff=1 is the specification where each year is treated as a period. Diff=2 is the specification where we treat two consecutive years to be a single period. We sum taxes, benefits, covered wages, GSP, interest credited to the trust fund for two consecutive years and treat that to be the value for a single period. Diff=3 is the specification where we treat three consecutive years to be a single period. Cash-on-hand is defined as [Trust fund balance + .01+ taxes-β*(unemp-meanunemp)*covered wages]. Income is defined as [Taxes-β*(unemp-meanunemp)*coveredwages]. β is the between state mean of β generated from a state panel regression of benefits/covered wages on unemp. Cash-on-hand and Income are divided by GSP. Ratio is Cash-on-hand/ Permanent Income. We define permanent income to be a 5 year moving average of income for Diff=1. For Diff=2 and Diff=3 we define permanent income to be a 3 period moving average of income. For Diff=2 and Start year=1976, the means of cash-on-hand, income, ratio and β are 0.85, 0.31, 3.21 and 0.0019 respectively. For Diff=3 and Start year=1976, the means of cash-on-hand, income, ratio and β are 0.78, 0.31, 2.90, 0.0018 respectively. For Diff=3 and Start year=1977, the means of cash-on-hand, income, ratio and β are 0.78, 0.31, 2.86 and 0.0018 respectively.

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