Capital Immobility and Regional Inequality: Evidence from India*

Siddharth Sharma†

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Abstract

There are striking, persistent regional inequalities in developing countries like China and India. I use district-level data on Indian factories to investigate if these disparities are related to the spatial immobility of capital. Employing a differences in differences strategy, I compare across districts the investment response to a 1998 policy change which expanded the set of factories eligible for a directed bank credit scheme. If capital is immobile then the returns to it, and hence this response, would be lower in wealthier districts. I find that districts which gained more from modern high-yield seeds released at the start of the agricultural "Green Revolution" in the late 1960s responded less to the 1998 credit shock, indicating that these districts- wealthier and more industrialized today- have lower returns to capital. The size of this differential effect suggests that a district at the 25th percentile of the initial HYV adoption distribution has 34% higher returns to capital than one at the 75th percentile. Thus, improving capital mobility will reduce regional inequalities and inefficiencies by directing investment to poorer, high-return districts.

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†Finance and Private Sector Development, The World Bank Group

1 Introduction

Recent studies have found enormous sub-national variation in the rates of return to the same factor in developing counties, indicating sizable capital and labor misallocation within these economies (Banerjee and Duflo (2005)). Hsieh and Klenow (2007) calculate that a hypothetical reallocation of capital and labor to equalize marginal products to the extent observed in the U.S. would lead to manufacturing TFP gains of 25-40% in China and 50-56% in India. These findings have special significance for research into the causes behind the persistence of regional inequalities in countries like China and India (Sachs et al. (2002), Pedroni and Yao (2006)), since they cast doubt on the common assumption that spatial investment patterns reflect the movement of factors to regions where they are scarce and command higher returns.

This paper examines the relationship between factor immobility and regional inequality in the context of industrialization in India. Industry is distributed very unevenly across Indian regions, and this geographic disparity has been rising in the last two decades (Aghion et al. (2005)). Data from the Annual Surveys of Industries indicate that in registered manufacturing, the fraction of national capital stock in the 10% most capital-intensive districts rose from 30% to nearly 60% between 1988 and 2000.[1]

The absence of convergence in China and India has been linked to regional differences in "fundamentals" like infrastructure, and to agglomeration economies (Sachs et al. (2002), Ahluvalia (2000), Au and Henderson (2006)). In theory, either can explain how spatial inequalities could endure despite factor mobility, but empirically, neither is easy to measure. This problem parallels the cross-country puzzle now known as the "Lucas Paradox": if the neoclassical model of diminishing returns is true, then the marginal product of capital in India should be several times that in capital-rich United States, and yet, U.S. capital does not flow to India (Lucas (1990)). Explanations for this puzzle attribute it to either international capital market imperfections, or missing fundamentals, which once included in the model would account for the apparent variance in returns. This debate continues because it is difficult to measure rates of return, and to control for unobserved variation in the quality of a factor (Bernard et al. (2005)).

Regional disparity in manufacturing may have serious welfare implications. Industrialization is strongly correlated with income and poverty rates across Indian districts (Figure 1), and there is evidence that workers in less developed districts are more susceptible to productivity shocks (Jayachandran (2006)). It also important, though, to distinguish between these two explanations, because the inequality associated with unequal returns to potentially mobile factors is inefficient, unlike that associated with missing fundamentals (Chaudhuri and Ravallion (2006)). Previous studies have tended to give mixed explanations, making it difficult to decipher the magnitude or direction of any optimal factor reallocation. But as I will

[1] Districts are the main administrative sub-units in Indian states. In 1961, the 13 major states of India contained 271 districts, with an average area of 8000 square kilometers and average population of 1.6 million each.

show, several facts about the Indian economy point to significant capital market imperfections. Smaller domestic firms finance their start-up and early growth mostly through internal funds, and borrow significant sums in traditional informal credit markets, where interest rates vary markedly across regions. Recent research indicates that even firms with a credit line from large commercial banks are credit constrained (Banerjee and Duflo (2008)). There is also a persistent cross-sectional correlation between district wealth and the level of industrial development, which suggests that savings are invested locally.

However, it is possible that interest rate variation across regions reflects variation in risk, or that industrialization is correlated with regional wealth because of stronger fundamentals in wealthier districts. I overcome this causality problem by exploiting a natural experiment, a nationwide increase in the supply of bank credit to a subset of firms in 1998. This was the result of a definitional change in the type of factories eligible for federally mandated directed credit from commercial banks. In India, factories with fixed investment below a certain level are classified as "Small Small Industry" (SSI), and are eligible for targeted bank credit through a quota system: a minimum percentage of a bank's total lending must go to a "priority" sector, which includes SSI. After the SSI ceiling was raised from Rs. 6.5 million to Rs. 30 million in 1998,[2] factories in the Rs. 6.5-30 million size range suddenly had access to priority sector credit. My approach is to infer if capital immobility is a cause of regional disparities by identifying if and how, in response to this shock, investment in factories differed across Indian districts.

I first present a simple model to explain the intuition behind this approach, which is that capital immobility would have led to persistent regional differences in the return to capital,[3] and districts where these returns were higher would have seen a larger investment response to the SSI redefinition. Thus, if capital immobility is the main reason for the persistent correlation between regional wealth and industrialization, then factories in the *less* wealthy districts would have expanded more. On the other hand, if capital is mobile, then there would not have been a systematic geographic variation in the response to the credit expansion.

In the empirical part of the paper, I investigate how the response to the shock varied across districts, after ordering them by a variable capturing their exposure to an agricultural shock in the late 1960s: their adoption rates of "High Yielding Varieties" (HYVs) of seeds released at the start of the "Green Revolution" in farming. The reasoning behind using this historical wealth shock instead of contemporaneous wealth to characterize districts is that the latter depends on recent growth trends, which makes its relationship to the district factory capital stock, or to the response to a credit shock, less reflective of persistent factor immobility. For instance, some districts could have become wealthier in the mid-nineties because their industrial composition was tilted towards industries that saw recent productivity jumps. These

[2] 1 Indian Rupee was approximately equal to $ 45 during this period.

[3] Bernard et al. (2005) gives evidence of factor price differences within the U.S. In neoclassical trade theory, sufficient heterogeneity in factor endowments plus factor immobility across regions can give rise to an equilibrium in which regions differ in relative factor prices.

districts would for the same reason have demanded more SSI credit, but this component of their response would not be indicative of any long-run factor immobility.

Some districts gained more than others in the early Green revolution because the first wave of HYV seeds worked better for their major crops and growing conditions (Munshi (2004)). Although HYV adoption and the resulting yield growth became more widespread over time as region-specific technologies were developed, early winners in the Green Revolution have stayed wealthier. I show that districts with higher initial HYV adoption were significantly wealthier on a per capita basis in the 1990s, and that they had a larger industrial and smaller agricultural sector, a pattern that strengthened during the decade. Moreover, this correlation of the sectoral composition of districts with early HYV adoption is similar too but stronger than that with contemporaneous district wealth, which supports the logic behind using a historical determinant of wealth.

Next, I estimate regressions measuring how the response to the SSI redefinition varied across high and low HYV adoption districts, employing a differences in differences strategy to identify the district-level investment response to the credit supply shock. Because the directed SSI credit was always available to factories below Rs. 6.5 million in value, I can control for other, geographically varying shocks to investment which were common to factories of different sizes by comparing, within districts, investment in the Rs. 6.5-30 million size range to that in the range below Rs. 6.5 million. I can also control for any persistent size-related differences in factory investment by comparing investment in the two size bands before and after the policy change. A (partial) rollback of the SSI definition change in 2000 allows me to verify that my results are not driven by trends in industrial investment that vary by district and by factory size.

I find that as predicted by capital immobility, districts with *lower* initial HYV adoption (or wealth) saw faster growth in the factory segment newly made eligible for SSI credit, relative to the segment that was already eligible for the directed credit. Moreover, this differential response lasted only for the duration of the credit shock, since low HYV adoption districts did not experience greater relative investment in the newly eligible factories after 2000, or before 1998. The estimated differential in the district response is large: the effect of the credit shock on the growth rate of factory capital in a district at the 25th percentile of the initial HYV adoption distribution was 135 percentage points higher than in a district at the 75th percentile. Under standard assumptions on the shape of the factory production function, I show that this differential implies that in the late 1990s, the return to investment in factories was about 34% higher in a district at the 25th percentile of the initial cross-sectional distribution of HYV adoption, compared to one at the 75th percentile.

The direction of this differential in the response implies that mobile capital will flow to low early HYV adoption districts: that is, to districts that are poorer and have less industry. The key policy implication is that improving capital mobility across regions would not only make inter-regional resource allocation more efficient, but also reduce regional inequality in incomes. This implication has special policy significance in the light of studies indicating that labor mobility is markedly low in India. For example, Munshi and Rosenzweig (2007) show that caste based insurance networks dampen incentives to migrate, and Topalova (2004) finds that the impact of India's trade liberalization on incomes depended on the initial industrial composition of a district. Given labor immobility, it may be that greater factory investment in low-wage areas, achieved through financial development, is the most effective way of lifting people living in less-developed regions out of poverty.

Besides the literature on spatial patterns of growth within developing countries, this study is related to the growing body of work on factor market imperfections, particulary those in capital markets, and the resulting variance in rates of return in developing countries. Recent papers have shown the existence of powerful credit networks, based on community or political connections, that favor network members over "outsiders" (Banerjee and Munshi (2004), Khwaja and Mian (2005)). Others have examined inefficiencies in bank lending, such as the political capture of banks (Cole (2007)), rigid lending by public sector banks (Banerjee et al. (2004)), and the effects of poor legal enforcement on loan recovery (Visaria (2005)). In this broad literature, the studies that are closest to mine in their methodology are those that use natural or controlled experiments to infer inefficiencies in capital allocation, or the existence of variable and high returns. Banerjee and Duflo (2008) show that firms granted credit because of the SSI redefinition in India borrowed and produced more, and conclude that the returns to capital in these firms must be at least 74%. McKenzie et al. (2008) use randomized grants to generate shocks to capital stock for Sri Lankan microenterprises, finding average real return to capital of 55-63 % per year.[4]

My paper contributes to this literature by using a natural experiment to uncover sizable capital allocation inefficiencies along the spatial dimension. I can also infer where (and by how much) returns are higher: in historically wealthier (or, high early HYV adoption) districts. This inference does not rely on any assumptions about how the determinants of manufacturing productivity vary across districts.

This paper is also related to the literature on the linkages between rural farm and non-farm growth (Lanjouw and Lanjouw (2001)). My finding suggests caution in drawing policy conclusions from cross-sectional correlations between agriculture and industry, since it implies that the association between a technology shock in agriculture and industrialization across Indian districts resulted from nothing other than a factor market inefficiency. Recent empirical research (Foster and Rosenzweig (2004)), in fact, suggests that agricultural growth raises local labor costs, making it optimal for factories to locate elsewhere. Thus, a policy focus on inter-sectoral linkages that ignores broader factor and product markets imperfections could perpetuate regional inefficiency and inequality.

[4]Duflo and M. Kremer (2008) use randomized trials in Kenya to find that rates of returns to using fertilizers varied from 169% to 500% depending on the year. Studies which show high rates of returns in non-experimental settings include Schundeln (2007), Anagol and Udry (2006), Goldstein and Udry (1999) and McKenzie and Woodruff (2003).

The remainder of the paper is organized as follows. Section 2 describes SSI policy and financing, and Section 3 HYV adoption in the Green Revolution. Section 4 illustrates the SSI redefinition, and presents a model of the district economy. This is followed by a description of data sources in Section 5, and a first look at the data in Section 6. Section 7 spells out the empirical specification and presents the results. In Section 8, I discuss how the results relating initial HYV adoption rates to the response to the SSI credit shock are to be interpreted, before concluding in Section 9.

2 Small-Scale Industry in India

2.1 Small-Scale Industries Policy

Smaller manufacturing establishments in India are classified as "Small Scale Industry" for policy purposes. The SSI category is defined by a ceiling on the current gross value of plant and machinery in an establishment, which is periodically raised on account of inflation.

Since the 1950s, India's industrial policy has supported the SSI sector in several ways. Certain products are "reserved" for the SSI sector, which means that they cannot be manufactured in factories that exceed the SSI size ceiling. SSI units are given tax concessions and other subsidies, and there is a large network of government institutions which specialize in providing marketing and technological support to small industry. Finally, as described below, there is an extensive credit support mechanism for small industries.[5]

2.2 Firm Financing in India

India's commercial banking sector is dominated by public banks[6] and very concentrated, with the largest 5% of banks housing nearly 70% of total bank deposits during 1990-2000.[7] The larger commercial banks have huge branch networks: in 2002, each of the 15 banks in the top 5% of deposit size had an average of about 2000 branches. The formal banking sector has wide geographic coverage, with more than 58,000 branches having been opened since the bank nationalizations in 1969. Moreover, due in part to a policy stress on rural banking (Pande and Burgess (2004)), by 2002 rural branches comprised about 40% of all branches for a top 5% commercial bank. These facts have an implication for how I will model the SSI credit shock: since most lending is by a few large banks with vast branch networks, it is reasonable to

[5]These policies share the general tenor of India's post-independence industrial policy, set by the desire to achieve self-sufficiency through import-substitution and a rigid set of controls (licenses) regulating the flow of private investment into industries. In the mid-1980s, and later in 1991, a series of reforms largely did away with license controls on factories (Kochhar et al. (2006), Chari (2008)), but SSI support policy did not see any dramatic revisions.

[6]The share of private banks in total bank branches remained at a fairly constant 10% between 1980 to 2000 (Banerjee et al. (2004)).

[7]Unless otherwise noted, figures in this section are based on the author's calculations, using data in R.B.I. (2008).

assume that the rates and loan amounts granted under special lending schemes follow similar, centralized procedures across districts.

Public sector banks are subject to strong regulation by the Reserve Bank of India (RBI), with rules specifying how much should be loaned to individual borrowers. One of the aims of the intense government oversight of formal sector lenders has been to ensure that credit is available to all sectors of the economy, in all regions. To this end, lending rules direct credit to a "priority" lending sector, which consists of SSI, agriculture and exporting, by imposing a quota on public and private bank lending. At least 40% of every commercial bank's credit must go to the priority sector, at an interest rate that is required to be no more than 4 percentage points above their prime lending rate (Banerjee and Duflo (2008)). Subject to this 40% overall quota, sometimes the government also sets sub-targets for specific priority sectors, including the SSI sector (Mohan (2001)).

The district is the centerpiece of India's "area approach" to targeted and focussed lending. Every district has a "Lead Bank", which coordinates priority sector lending by all banks in that district, and has to ensure that the priority sector quota is met within the district.[8] In addition, there are term lending institutions that lend exclusively to the SSI sector,[9] and these too have an office in most districts.

Despite these schemes, Indian firms- particularly small and medium ones- have been found to rely heavily on self-financing and informal credit (Love and Peria (2005), Allen et al. (2006)). A 2005 World Bank survey of Indian enterprises shows that firms with fewer than 20 workers finance about 15% of working capital and 19% of investment capital from friends, family or "informal sources". These firms are also heavy users of internal funds for both working (62%) and investment capital (59%).[10]

Besides friends and family, India's unregulated credit sector consists of traditional village moneylenders, small "finance companies", *nidhis* (informal credit institutions) and "chit funds" (rotating savings and credit associations). Credit also flows through social networks based on ethnicity or caste, such as those among the *Marwari* community of traders and industrialists. It could be that informal credit is in such extensive use because it is cheaper or more convenient than bank credit, but surveys of informal credit markets indicate that interest rates in the informal sector are *higher* than those charged by banks (Timberg (1978), Aleem (1990) and Dasgupta (1989)). These facts tie in with the growing literature on the micro-economics of credit market failures in India (Banerjee et al. (2004)), whose findings on under-lending by formal banks suggest a demand spill-over into informal markets.

Unlike banks, informal credit markets are local to cities, towns or rural communities. Timberg and Aiyar (1984) find substantially different interest rates across cities, even within

[8]Recommendations of the 1969 Nariman Committee, Reserve Bank of India.

[9]Such as the Small Industries Development Bank of India (SIDBI), and the National Bank for Agricultural and Rural Development (NABARD) (S.I.D.B.I. (2001)).

[10]These are establishments below the 60th percentile of firm employment in the sample. Source: 2005 India Manufacturing Survey at *http://www.enterprisesurveys.org/*.

the same community of lenders. In Banerjee and Munshi (2004), which investigates community-based credit networks in the textile industry in Tirupur, new firms belonging to the established local community are shown to start off with more capital than the "outsiders", despite poorer performance. And yet, many of the outsider firms belong to communities well-established in business elsewhere, which suggests that social credit networks do not function over long distances.

I used firm-level borrowing data from a nationwide survey of small firms to estimate district averages of actual interest rates being paid by firms in 1994.[11] Figure 2 presents the cross-district spread in the mean annual interest payment, expressed as a percentage of the outstanding loan amount, for formal and informal loans in four industries. It shows that formal interest rates are lower and more spread out than informal rates, in each industry. Moreover, there is a negative correlation between informal sector interest rates and district wealth, and no such relationship between formal rates and wealth. While this is in keeping with the intuition that with capital immobility, wealthier districts would have cheaper informal credit, these differences in nominal rates might reflect those in lending costs or risk. A causal inference requires studying the response to a credit shock which is similar across districts, as I explain in Section 4.

3 HYV Adoption in the Indian Green Revolution

The start of the Green Revolution in the developing world is associated with the introduction of HYVs of major crops like rice and wheat in the late 1960s. With their adoption, parts of India saw dramatic increases in farm yields- but not all regions shared in these early gains.[12] There is because modern varieties were released at different times for different crops, and because the earliest ones varied in their suitability across dissimilar growing conditions.

The first HYV seeds introduced in India were hybrid varieties of wheat (in 1967) and rice (in 1966), together with some coarse grains like sorghum, maize and millet. Hence, early HYV adoption in an area depended firstly on the acreage already under one of these crops. The traditionally wheat growing regions- the Northwest Plains, the Northeast Plains and the Central Peninsular Zone- all saw relatively rapid advances in early HYV adoption, since the wheat varieties proved to be relatively robust in their success across sub-regions. Unlike wheat, the first rice (and coarse grains) HYVs proved to be sensitive to local conditions and deseases. Hence early on, Indian scientists started developing rice HYVs to suit specific areas, which led to over one-hundred locally-robust HYVs varieties being released before 1980, with 28 such varieties released as early as 1970. By 1971, about 35% of wheat, 10% of rice, and 5% each of sorghum, maize and millet acreage was under HYVs. The total acreage planted to HYV rice and wheat was 5 million hectares each, with 1.5 million hectares planted to HYVs of coarse

[11] Survey of Unorganized Manufacturers, National Sample Survey Organization. Because of patchy loan data in the survey, this is a sub sample of districts used in the rest of this paper.

[12] This section is based on Munshi (2004), Evenson et al. (1999) and Gollin and Evenson (2003).

grains. Figure 10 maps these initial HYV adoption rates in Indian districts. The rates are highest among the traditionally wheat growing districts of the Northern plains and some of the rice districts in Southern and Eastern India, but there is marked inter and intra-regional variation.[13]

Green Revolution technology became equitable with time, with area-specific innovation and expanded irrigation. Regional dispersion in agricultural yields has been in decline since the early 1980s (Sawant and Achutan (1995)), and HYVs have now spread to almost all the areas of India with irrigation or assured rainfall and no flooding. In 1993, about 70% of rice, 90% of wheat and 50% of coarse grains acreage was under HYVs. Nonetheless, it is well documented that the early adoption variation widened regional income disparities in India, with assets rising faster in high adoption areas (Munshi and Rosenzweig (2007)).

4 Theoretical Model

4.1 The SSI Redefinition

In January 1998, the central government changed the definition of a small scale factory, raising the SSI ceiling from Rs 6.5 million in gross value of plant and machinery to Rs 30 million. Following this, I label factories with gross value of plant and machinery below than Rs 6.5 million *Small*, and those between Rs 6.5 million and 30 million *Medium*.

The official justification for directing credit to small firms, which accords with recent cross-country data on bank lending in developing countries (Beck et al. (2008)), is that banks prefer lending to larger firms. This suggests that the redefinition would have increased the availability of bank credit to the larger of the SSI factories- the *Medium* factories. Moreover, after 1998 an entrepreneur planning to set up a new factory in the *Medium* size range could borrow from term-lending institutions that lend exclusively to the SSI sector.[14] Banerjee and Duflo (2008) find strong evidence in bank loans data that the SSI redefinition did increase credit supply to *Medium* establishments. They also find that the shock had a significant impact on the "treated" firms' output, which suggests that newly eligible firms did not just use the SSI loan to pay back older loans.

Below, I present a simple two-sector model of a district economy, to illustrate what spatial immobility implies for the cross-district distribution of marginal returns to a factor, and how the SSI redefinition can be used to test for this.

4.2 Capital Immobility and The District Economy

This district economy model is a static one, intended to describe a long-run equilibrium characterized by efficient within-district allocation of capital. The main intuition is that if there

[13]Section 7.3 shows that my results are robust to focussing on within-state variation.

[14]Informal interviews with bank branch managers of large commercial banks, and officials of SIDBI and NABARD in New Delhi.

are diminishing returns, then conditional on total factor productivity in the district, higher district supply of a factor implies lower district returns to that factor. Hence, if the factor were spatially mobile, it would disperse more evenly across districts.

There are two sectors, agriculture and manufacturing, and two factors of production, labor l and capital k, the latter used exclusively in the manufacturing sector. It is assumed that capital and labor cannot cross district boundaries, which implies that district investment in determined by local wealth:[15]

Assumption 1 *The district has a fixed amount of total capital in the manufacturing sector, exogenously determined by per capita assets W and population P.*

The agricultural sector has CRS technology with productivity b, so that the output of a farm with labor input l_f is given by

$$q_f = bl_f \tag{1}$$

As in Foster and Rosenzweig (2004), the agricultural good is traded with the outside world at a price p_f. Thus, the equilibrium wage rate in the district is determined by agricultural productivity, and can be taken as a given in analyzing the manufacturing sector:[16]

$$w = bp_f \tag{2}$$

The manufacturing sector consists of multiple production units or "factories". A factory i, with total factor productivity (TFP) level $\tilde{a}_i$, uses capital k_i and labor l_i to produce output q_i given by

$$q_i = \tilde{a}_i {k_i}^{\alpha} {l_i}^{\beta} \tag{3}$$

I rely on decreasing returns to scale at the factory level to obtain a non-degenerate size distribution of factories: $\alpha + \beta < 1$. I also assume that the factory output, which is the numeraire commodity, is traded freely across districts. Let r denote the price of capital in the district, or the interest rate, which individual factories take as given. Efficient capital markets and profit maximization by factories imply that in equilibrium, the marginal returns to k in every factory will be equal to the district interest rate,

$$\alpha \tilde{a}_i l^{\beta} k_i^{*\alpha - 1} = r \tag{4}$$

In equilibrium, factories with higher productivity are larger: plugging the optimal labor choice

[15] This assumption ignores, for the sake of tractability, the modern banking sector, through which savings can move across regions. As noted earlier, survey data indicate that as much as 80% of investment capital in small and medium-sized Indian firms is from informal sources and internal funds.

[16] The CRS assumption, or even labor immobility are not critical to the main prediction of the model, and are intended to demonstrate in the simplest way that labor costs depend on agrarian conditions. Perfect labor mobility is equivalent to assuming CRS technology with no differences in agricultural productivity b across districts. Labor immobility with decreasing returns in agriculture implies an upward sloping labor supply curve to manufacturing, which would only strengthen the model's prediction about a negative relationship between local wealth and returns to capital.

condition into Equation 4 solves for the optimal factory size,

$$k_i^* = \left(\frac{a_i}{r}\right)^\tau \tag{5}$$

Here, a_i is a relabeled productivity term which depends on TFP $\tilde{a}_i$ *and* labor cost w:

$$a_i = \alpha \tilde{a}_i^{\frac{1}{1-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\beta}} \tag{6}$$

and

$$\tau = \frac{1-\beta}{1-\alpha-\beta} \tag{7}$$

I now solve for the equilibrium interest rate, which will depend on the total factory demand for capital, and the district supply of capital, PW. Let G(.) be the cumulative distribution function of manufacturing productivity a_i, with support $[a_{max}, a_{min}]$, and N the mass of factories in the district. The capital market clearing condition for the district is

$$N \int_{a_{min}}^{a_{max}} k_i^*(a_i, r) dG(a_i) = PW \tag{8}$$

I assume that G(.) is a uniform distribution, with a mean m and support of length $2n$, so that $a_{max} = m + n$ and $a_{min} = m - n$. N, the mass of firms, is exogenously determined by the supply of "entrepreneurial talent" in a district, which is a fixed fraction $\frac{1}{c}$ of the district population size P. This assumption implies that PW/N, the average capital available to a factory, is a linear and increasing function of per capita assets W. Thus, the capital market clearing condition simplifies to

$$\int_{m-n}^{m+n} k_i^*(a_i, r) dG(a_i) = cW \tag{9}$$

Equation 9, and the fact that G(.) is a uniform distribution imply the district equilibrium interest rate r^* is given by:

$$r^* = \left(\frac{1}{cW}\right)^{\frac{1}{\tau}} Z \tag{10}$$

where

$$Z = \left[\frac{(m+n)^{1+\tau} - (m-n)^{1+\tau}}{2n(1+\tau)}\right]^{\frac{1}{\tau}} \tag{11}$$

Equation 10 shows how r^*, the marginal return to investment, varies across districts in a world where district capital is immobile. Notably, the partial derivative of r^* with respect to W indicates that given the distribution of a_i, wealthier districts have lower returns to capital:

Proposition 1 *The district marginal return to capital is decreasing in district per capita wealth W.*

Equations 10 and 11 also show that conditional on wealth,

Proposition 2 *The marginal return to capital is increasing in average manufacturing productivity m.*

The model thus says that if capital is immobile and there are diminishing returns, then wealthier districts have lower r^*, unless they have systematically higher productivity a_i.[17] Note that manufacturing productivity, as defined here, is inclusive of district labor cost w (equation 6), which is increasing in agricultural productivity. More generally, m may reflect cross-district differences in the supply of factory inputs other than capital, such as roads and ports, or even agglomeration effects.

4.3 The Response to an Exogenous Credit Supply Expansion

The SSI redefinition increased the availability of bank credit to factories of a certain size, and this credit was made available in all districts at the same below-market rate (Banerjee and Duflo (2008)). So I model the credit supply shock in this manner: after a credit policy change, any factory of size $k \in [k_s, k_t]$ (a $Medium$ factory) can expand by borrowing unlimited sums from banks, at a rate r_{ssi}. Then, I ask how this borrowing affects investment in the $Medium$ factory segment, in a district with pre-policy change equilibrium interest rate r^*. Because only a minor subset of factories is directly affected, this exercise ignores the general equilibrium effects of the credit expansion on the prices of other factors.

First, Equation 5 implies that targeting factories of size $k \in [k_s, k_t]$ is equivalent to targeting factories with productivity $a_i \in [a_s, a_t]$, where these bounds depend on district equilibrium r^*:

$$a_j = k_j^{\frac{1}{\tau}} r^* \tag{12}$$

for $j = s, t$.[18]If $r_{ssi} \geq r^*$, then no factories demands the SSI credit. But if $r_{ssi} < r^*$, then each $Medium$ factory i borrows from banks and expands until

$$k_i = \left(\frac{a_i}{r_{ssi}}\right)^{\tau} \tag{13}$$

Here, the assumption is that the newly available loan cannot be used by the targeted medium-sized factories to substitute for existing loans.

Equation 13 implies that after the credit supply expansion, in what I call the "post"

[17] Here, diminishing returns at the factory level lead to aggregate diminishing returns as long as there are lower bounds on factory size. Hence the assumption that the number of units is limited by the local supply of entrepreneurs- but fixed costs or a minimum scale would also justify a lower bound. Moreover, even without diminishing returns at the plant level, returns to aggregate capital would be diminishing if the district supply of other factors or inputs were inelastic.

[18] That is, each $Medium$ factory in a low r^* district has lower TFP than a factory of the same size in a higher r^* district.

period, total investment in the targeted factory range is given by

$$\begin{aligned} Medium_{post} &= \int_{a_s}^{a_t} \left(\frac{a_i}{r_{ssi}}\right)^{\tau} dG(a_i) \\ &= \left(\frac{N}{1+\tau}\right)\left(\frac{1}{r_{ssi}}\right)^{\tau}\left[\frac{{a_t}^{1+\tau} - {a_s}^{1+\tau}}{2n}\right] \end{aligned} \tag{14}$$

Total investment in the *Medium* segment before the credit expansion was

$$\begin{aligned} Medium_{pre} &= \int_{a_s}^{a_t} \left(\frac{a_i}{r^*}\right)^{\tau} dG(a_i) \\ &= \left(\frac{N}{1+\tau}\right)\left(\frac{1}{r^*}\right)^{\tau}\left[\frac{{a_t}^{1+\tau} - {a_s}^{1+\tau}}{2n}\right] \end{aligned} \tag{15}$$

It is easily shown that

$$log(Medium_{post}) - log(Medium_{pre}) = \tau[log(r^*) - log(r_{ssi})] \tag{16}$$

Proposition 3 *The proportional expansion of the Medium factory segment in response to an expansion in bank credit supply is larger the higher the pre-1998 district returns to capital.*[19]

In combination with Proposition 1, this says that if capital is not mobile across districts, then the *Medium* sector expands more in lower wealth districts, unless richer districts happen to have higher productivity a_i.

Note that the model describes the "short-run" effect of the credit shock, in the sense that it takes the set of factories as fixed, ignoring entry. In the long-run, the increased availability of bank credit would have encouraged more entry into the *Medium* segment than would have occurred otherwise. Because the cheap credit would matter more where local capital was more expensive, this redirection of entry would have been greater in districts with higher returns, which is as the model predicts. Second, it is possible that the SSI scheme distorted the size distribution by discouraging firms with optimum sizes marginally larger than the older SSI ceiling from crossing the ceiling. After the redefinition, some of these would have expanded into the *Medium* category. Since the SSI subsidy was more valuable the higher the local cost of capital, it is likely that this distortion (and its post-1998 correction) too would have been greater in districts with higher returns. Thus, even after allowing for entry effects, a systematic difference across districts in the credit shock response is indicative of differential credit availability. This is significant because given the absence of panel data on factories, I cannot distinguish between expansion and entry in the overall response to the credit supply shock.

Suppose that contrary to the findings in Banerjee and Duflo (2008), the new SSI loans were used by firms to substitute for older loans. This means that some of the new SSI "capital" to *Medium* establishments was transferred to other factories in the same district, and that

[19] It can be shown that even the absolute increase will be higher in districts with higher r^*, the intuition being that each medium-sized factory in a low r^* district has lower TFP than a factory of the same size in a higher r^* district.

increased borrowing by the targeted firms did necessarily translate into increases in *their* investment. My empirical results will suggest that this is not a big concern, since I find that the post-1998 within-district patterns in investment in the *Medium* segment mirror that in its borrowing. Nonetheless, it is worth noting that substitution of debt implies that measuring the response to the SSI redefinition by focussing on the *Medium* segment underestimates it.

4.4 Perfect Capital Mobility

Suppose k is perfectly mobile across district, which implies that there is no district capital market clearing condition to be met, and that factories in every district borrow at the same interest rate. Profit maximization in factories then ensures that the marginal returns to capital are the same not just within but also *across* districts, regardless of any differences in underlying productivity (or wages). Now, the expression in Equation 16 is independent of the distribution of productivity a_i, which indicates that the proportional response to the credit shock would not have varied systematically across rich and poor districts if capital were perfectly mobile.

Perfect capital mobility also has different implications for the sectoral composition of districts. As Equation 5 shows, if the interest rate is identical across districts, then more productive districts have larger factories and hence more total factory capital, regardless of their wealth. District manufacturing employment therefore rises, and agricultural employment falls, in mean a_i. If wealthier districts happen to have more investment, it must be because district manufacturing productivity is positively correlated with wealth (or, district agricultural productivity negatively correlated with wealth).

5 The Data

The principal source of the data used in this paper is India's Annual Survey of Industries (ASI), a cross-sectional, representative survey of "factory establishments" conducted by the Central Statistical Organization of India. India's Factory Act defines a factory as a manufacturing establishment that employs at least 10 workers if it uses power, and at least 20 workers if it does not. The ASI does a census of factories employing 100 workers or more, and samples nearly a quarter of all the remaining registered factories, with every state and 3-digit industry constituting a survey strata. I used ASI data for the years 1988, 1994, 1998, 2000 and 2002 to estimate for every district the number of establishments, total employment, output, borrowing and investment, in each factory size category.

Some concerns with using ASI data are that the survey does not include establishments with fewer than 10 workers, and that it may underreport employment and value added (Nagaraj (1999)). It is, however, extremely unlikely that units with plant and machinery worth Rs. 30 million (nearly 0.75 million USD) would employ less than 10 workers in India. And more importantly, given my differences in differences strategy, any underreporting in ASI would not affect my main results, unless the reporting bias changed differentially across high and low HYV adoption districts during the 1990s.

I supplemented the ASI data using three other data sources. In order to measure mean per capita household assets at the district level, I used the 1992 All India Debt and Investment Survey (AIDIS), a large household survey conducted by the National Sample Survey Organization (NSSO), which elicited asset holdings as of April 1992 and was stratified by district.[20] The logarithm of this estimate of district per capita assets is called *Wealth* throughout this paper. Next, I used the World Bank India Agricultural and Climate Data Set (Sanghi et al. (2004)), which contains annual agricultural acreage and output data, over 1958-87, on all major crops in 271 districts. The districts, defined by their 1961 boundaries, are from 13 major states which together cover more than 85% of India's land area.[21] This data set is the source of the variable $HYV71$, which is the logarithm of the fraction of district cultivated area planted to HYV seeds (of thirteen major crops) during 1968-71. I also used it for estimating district yields, and for measures of district characteristics like irrigated area and road length. Lastly, I used data from the NSSO's Employment and Unemployment Surveys, which are large household surveys conducted every five years. The surveys are stratified by district, and collect information on household members' employment and education, which I used to measure district sectoral employment and literacy.

In merging the district-level data from these sources, I consolidated it at the level of districts as they were defined in 1961. Hence, there is complete data for all 271 districts (1961 boundary definition) in the 13 states covered by the India Agricultural Data Set. Since many of these districts have since split into multiple districts, this sample covers about 350 districts according to their 2001 boundaries.

6 Descriptive Statistics

Table 1 summarizes the district-level data used in this paper. On average, a district had 364 registered manufacturing units in 1994, of which 316 were *Small*, 24 *Medium* and 23 *Large* (that is, with plant and machinery greater than Rs. 30 million). Of the total district factory employment of 20,000 full-time workers, 41% was in *Small*, 12% in *Medium* and 47% in *Large* factories. About 20% of the average district factory output of Rs. 12,602 million was produced in *Small* factories, 12% in *Medium* and 68% in *Large* factories. Larger factories borrow disproportionately larger amounts: only 12% of total outstanding loans were taken by *Small* and *Medium* factories.[22]

[20] AIDIS 1992 was the earliest available district-level asset data based on a household survey. Assets reported are land, building, household durables and financial assets. AIDIS data show that financial assets are a small portion of household assets in India, particularly in rural areas, suggesting that the formal financial sector plays a minor role in mobilizing savings in rural India.

[21] The 13 states are Haryana, Punjab, Uttar Pradesh, Gujarat, Rajasthan, Bihar, Orissa, West Bengal, Andhra Pradesh, Tamil Nadu, Karnataka, Maharashtra and Madhya Pradesh.

[22] The factory sector employs a small share of India's workforce, relative to its contribution to GDP. In 1994, factory employment on average constituted about 5% of a district's total wage employment. In contrast, even

The shares of the three size categories in the factory sector remained stable between 1994 and 2000, even as the total number of factories, output and value added increased. Table 1 also shows that there was considerable dispersion across districts in the size of the factory sector. Finally, the mean initial HYV adoption rate across these 271 districts was 10.2% of cultivated area, and as measured by AIDIS in 1992, the average value of per capita assets was Rs. 24000, nearly twice the value of Indian GDP per capita.[23]

6.1 Wealth, Initial HYV Adoption and Sectoral Composition

Table 2 shows how district characteristics vary cross-sectionally by mean district per capita assets, presenting 1994 ASI summary statistics after splitting districts into those below ("low") and above ("high") median per capita wealth. The upper panel looks at all factories, while the lower panel restricts attention to *Small* and *Medium* factories. In both panels, but more so when restricting attention to *Small* and *Medium* factories, the statistics on the number of factories, investment and output show that poorer districts had a smaller factory sector. For example, on average a high wealth district had 15% higher total factory capital and 37% higher *Small* and *Medium* factory capital than a low wealth district. Given the high variance in these statistics, however, they should be read them with caution.

The relationship between district wealth and the size of the manufacturing sector is more apparent in Figure 3, which presents non-parametric Kernel (Nadaraya-Watson) regressions of 1988 district sectoral characteristics on the logarithm of district mean per capita assets, with bootstrapped 10% confidence intervals.[24] These show that the factory sector was larger in wealthier districts, when measured by the number of factories, output or share in district employment. The factory sector's share in total district employment, for instance, almost triples as one moves from low to high wealth districts. In contrast, as the bottom-right panel of Figure 3 shows, the agricultural sector's share in district employment was lower in wealthier districts. These sectoral patterns- that wealthier districts had a larger manufacturing sector and a smaller agricultural sector- have endured throughout the 1990s, and if anything, become more accentuated. Figure 4, which presents non-parametric regressions of *changes* in the district sectoral composition over 1988-2000, suggests that the factory sector grew more in wealthier districts, while agricultural employment did so in poorer districts.

Next, I consider the relationship between initial HYV adoption and wealth. Panel A in Figure 5 presents Kernel regression estimates of the correlation between district initial HYV adoption and average per capita assets in 1992 (in logarithms). District per capita assets increase by nearly 40% as we move from the lowest to the highest early HYV adoption districts. Panel B graphs Kernel regression estimates of the deviations of $HYV71$ and district per capita

in *Small* factories, mean value added per worker was 4 times GDP per capita.

[23] All values, including assets, are expressed in 1994 prices, deflated using the Wholesale Price Index for India.

[24] I could not include the 1988 ASI data in the main regressions because of comparability issues in a critical variable- the value of plant and machinery. The graphs and preliminary regression results in this section are insensitive to using 1988 or 1994 ASI data.

assets from their respective state averages, demonstrating that this relationship is robust to focussing on within-state correlations. Panel A in Table 4 presents a regression of $HYV71$, the logarithm of the initial HYV adoption rate, on the logarithm of district per capita assets. The coefficient on $HYV71$ is positive and statistically significant, implying that a unit increase in $HYV71$ is associated with a nearly 10% rise in mean per capita assets.

Finally, I look at initial HYV adoption and district sectoral characteristics. Table 3 summarizes the 1994 ASI district-level data after splitting districts into two groups: those below ("low") and those above median ("high") initial HYV adoption. The patterns are similar to but stronger than those seen in Table 2, which compared low and high wealth districts: high HYV adoption districts had a substantially larger factory sector, on all counts.

The Kernel regressions in Figure 6 reiterate the positive relationship between district initial HYV adoption and the size of the manufacturing sector. In 1988, the number of establishments, total output and percentage employment in the factory sector were all uniformly higher in districts with higher initial HYV adoption rates. In contrast, agriculture's share in employment was lower in high adoption regions, falling uniformly from 45% to 30% across the 271 districts. Thus, these relationships are similar to those seen with wealth (Figure 3), but steeper and tighter. They too are strengthening over time: as Figure 7 shows, high initial HYV districts experienced larger increases in the number of factories and factory output.

To reemphasize these patterns, in Panel B, Table 4, I regress district employment by sector (in 1988 and 2000) on $HYV71$. The coefficient on $HYV71$ measures the cross-sectional relationship between $HYV71$ and a sector's employment share, while that on its interaction with the year 2000 dummy measures how this relationship changed over time. The estimates imply that as one moves to higher HYV adoption districts, the share of district workforce working in factories and in self-employment rises, while that in agriculture and services falls. Thus, high adoption districts have larger workforces in the relatively capital intensive sectors, and not in the sector that initially gained from the HYV adoption. The $HYV71 * Year2000$ coefficients are not statistically significant, implying persistence.

Overall, these graphs and tables suggest that increases in per capita household wealth in the early years of the Green Revolution are systematically associated with a larger factory sector, and smaller agricultural sector, in the 1980s and 1990s. Moreover, the sectoral composition's relationship with initial HYV adoption is stronger than that with contemporaneous wealth, in keeping with the hypothesis that early wealth divergence is a better indicator of the effects of capital immobility than current wealth.

7 Empirical Results

7.1 Empirical Specification

The model in Section 4 showed that if capital has been immobile, then the response to a credit supply shock would vary across districts, because of differences in their returns to capital, related to differences in local wealth. Since the Green Revolution led to a sustained divergence in wealth across high and low adopters of first-wave HYVs, with long-run capital immobility low initial HYV adoption regions are expected to respond more to a credit expansion. The core regressions in this paper test this by comparing the investment effect of the SSI redefinition across high and low initial adoption districts.

Let j denote district, t year , and c the the factory segment, with $c \in \{Small, Medium\}$. In the main regressions, I use data on factory sector growth over two periods, 1994-1998 and 1998-2000. Let $Post_t$ be a dummy that equals one for 1998-2000, the years immediately after the SSI redefinition. Let X_{cjt} be the annual *growth* in the factory segment c in district j during period t, measured as the increase in the logarithm of a levels measure x_c.

The district response to the credit supply shock is measured by the expansion of the "treated" segment ($Medium$) in the post-1998 period, relative to the pre-1998 period. I can control for district-specific productivity shocks to industry by comparing the growth rates of the $Medium$ and $Small$ segments, which then leads to a differences-in-differences type estimator of the average district response to the SSI credit shock, a_2:

$$X_{cjt} = a_1 Med_c + a_2 Post_t * Med_c + \delta_{jt} + u_{cjt} \tag{17}$$

where δ_{jt} is a district-year fixed effect, and Med is short for $Medium$. a_2 measures the effect of the shock ($Post_t$) on the treated factory segment, relative to the already eligible segment, $Small$. This paper's focus, however, is on how this effect varied across districts. To estimate that, I modify Equation 17 to allow the response to vary by the initial HYV adoption rate of the district:

$$X_{cjt} = a_1 Med_c + a_2 Post_t * Med_c + a_3 HYV71_j * Med_c + b HYV71_j * Post_t * Med_c + \delta_{jt} + u_{cjt} \tag{18}$$

The coefficient of interest is b, which measures how the post-1998 expansion of the $Medium$ segment, relative to the $Small$ segment and to the pre-1998 period, depended on district initial HYV adoption $HYV71$. A negative estimate of b would indicate that the effect of the shock was greater in capital-poor low HYV adoption districts, implying that lower adoption districts have higher returns to capital.

Shocks correlated with $HYV71$ could bias the estimate of b- but note that δ_{jt} controls for any district-specific shock common to the growth of *Medium* and *Small* factories. Thus, b gives the relationship between $HYV71$ and the district response to the credit shock under the identification assumption that post-1998 changes in other determinants of the growth of the *Medium* segment, *relative* to *Small*, did not vary systematically by $HYV71$. Since this assumption would be violated if the trend in the relative growths of *Medium* and *Small* factories varied by $HYV71$, I will present evidence against such a divergent trend in section 7.4.

7.2 The Main Results

Tables 5 and 6 present the main empirical results of this paper: OLS estimates of equation 18, where the outcome variables are district-level growth in various indicators of the size of the *Small* and *Medium* segments of the factory sector. In Table 5, Columns (1)-(4), these indicators are, respectively, the number of factories, the total value of fixed capital, of plant and machinery, and total employment. Each observation in these regressions corresponds to a factory segment (*Small* or *Medium*) in a district during either 1994-98 or 1998-2000 (*Post*), with the outcome variable measuring average annual growth (in logs) during that period.

The central result in Table 5 is that the coefficient on $HYV71 * Post * Medium$ is negative, and consistently so across all four measures. In column (1), where the outcome is growth in the number of factories, this coefficient is estimated to be -0.275, significant at the 1% level. This implies that in the two years after 1998, and compared to the pre-1998 period, the annual increase in the number of $Medium$ factories relative to $Small$ factories was higher in districts with *lower* initial HYV adoption. To get a sense of the magnitudes, consider this: the point estimate of b implies that lowering $HYV71$ by 1.5 points, the difference between the 75th and 25th percentile of the $HYV71$ distribution, increases the coefficient on $Post * Medium$ by 0.41. Thus, the effect of the SSI credit shock on growth in the number of factories in a district at the 25th percentile of the initial HYV adoption distribution was 41 percentage points higher than in a district at the 75th percentile. Similarly, the coefficient value of -.9 on $HYV71 * Post * Medium$ in columns (2) indicates that lowering $HYV71$ from the 75th to the 25th percentile raises the impact of the credit shock on the growth rate of fixed capital by 135 points. For employment, the corresponding differential is 55 points.

The result for growth in the number of factories suggests that in part, the response to the credit shock took the form of entry into the $Medium$ segment: that is, new firms set up with plant and machinery in the Rs. 6.5-30 million range, or existing $Small$ factories expanding into the $Medium$ range. The $HYV71 * Post * Medium$ coefficient on total fixed capital (column (2)) is higher than that on the number of factories (column (1)), suggesting that expansion in existing $Medium$ factories too was a significant part of the response.

Table 6 presents the same regressions as Table 5, but with different outcome variables: growth in outstanding loans, revenue, factor payments and value added. The results tally with those in the previous regressions. In column (1), which looks at the growth rate of outstanding loans, the coefficient on $HYV71 * Post * Medium$ is -.572, significant at the 5% level, indicating that the relative increase in borrowing by $Medium$ factories was higher in low $HYV71$ districts. This is consistent with the hypothesis that the differential expansion of the $Medium$ sector across districts is driven by a differential uptake of new SSI scheme credit. In column (2), the negative estimate of b indicates that the post-1998 relative increase in the growth rate of revenue in the treated factory segment was 112 points higher in a 25th percentile district, compared to one at the 75th percentile. Finally, the results for factor payments and value added are similar, though weaker.[25]

7.3 Robustness Tests

India's SSI policy encompasses several benefits or subsidies besides prioritized credit (Mohan (2001)). Small scale units benefit from fiscal concessions through lower excise duty rates, special procurement and "price preference" programs, and government technology and marketing support, with about 30 Small Industries Service Institutes providing technical support to SSI units across the country. Could these elements of the SSI policy, rather than directed credit, be behind the differential response seen above? To do so, they would have to matter more to factories in poorer districts. But subsidies such as fiscal concessions, which do not change the price of a factor or input, would have the same effect across districts. Studies also indicate that technical and marketing support to the SSI sector has not been of great value to small firms (Mohan (2001)), and is therefore not likely to matter to the entry or expansion of the larger SSI units.

A more serious concern arises from the policy of reserving certain product classes for small scale factories, because in those products, the easing of the SSI ceiling would have removed entry restrictions on $Medium$ establishments. This would affect my results if the manufacture of products reserved for SSI was concentrated in some districts, and this pattern of concentration was correlated with a district's early HYV adoption. About 80 percent of the products reserved for SSI are in 11 of the standard 130 3-digit industry groups in manufacturing.[26] So, I can test against this alternative by re-estimating Equation 18 after dropping factories belonging to those 11 industry groups from the sample. The results, presented in the first three columns of Table 7, indicate the product reservation had nothing to do with the differential response to the SSI redefinition: for every outcome, the estimates of the coefficient on $HYV71 * Post * Medium$ are negative, statistically significant and of the same magnitudes as the corresponding unrestricted sample estimates in Table 5.[27]

Ever since the Industrial Policy Resolution of 1956, which reserved certain industries

[25] This could be a data quality issue: about 10% of observations had negative total value added, which also explains the lower number of observations in the last two columns.

[26] These are: Knitting in mills; Manufacture of plastic products; Manufacture of basic and industrial organic and inorganic chemicals; Paints, varnishes and lacquers; Photochemicals and sensitized fibres; Fabricated metal products, metal boxes, cans safes and vaults; Hand tools and general hardware; Electrical appliances, domestic appliances, switches and sockets; Auto parts; Bicycle, rickshaws and parts; Mathematical and miscellaneous instruments (Mohan (2001)).

[27] For the sake of economy, in Table 7 and in the rest of the robustness checks, I show results for a subset of the outcomes examined in the main results. Results for other outcomes are similar.

for public sector monopoly and others for public sector dominance, India has had significant public ownership in industry. In 1994, about 8% of all ASI factories in each size class were in the public sector. In the 1956 policy, major objectives of setting up public enterprises included the promotion of balanced regional development, and the development of small scale industries.[28] This suggests that official policy might have "subsidized" industry in less-developed areas through public investment, and that there might be more small-scale public sector units, dependent on subsidized credit, in poorer districts. If so, and if public banks prefer lending to public sector units, then an expansion in publicly owned factories could be why low $HYV71$ districts responded more to the credit shock. In that case, my results would not reflect the private returns to capital across districts. I tested against this by dropping public sector firms from the sample and re-running regression 18. The results, presented in Table 7, columns (4)-(6), are similar to those on the unrestricted sample, which implies that preferential SSI credit to public sector enterprises, if any, is not driving the main result.

India is a federal democracy and consequently, some laws and policies vary across states. For instance, some states have more "pro-worker" labor laws than others, making it more difficult to fire workers (Besley and Burgess (2004)). Because labor regulation can increase the importance of hold-up problems in investment, this state-level variation in the strength of labor laws might matter in the response of industrial investment to other policy changes. For example, Aghion et al. (2008) find that following delicensing, industries located in states with pro-employer labor market institutions grew more quickly than those in pro-worker environments. It is therefore possible that the spatial pattern in the response to the SSI policy change reflects a correlation between early Green Revolution gains and state-level differences in policies and institutions. However, as Table 8, columns (1)-(3) show, my results are robust to focussing on within-state correlations in the initial HYV adoption and the response to the credit shock. Here, I re-estimate Equation 18 with a modification that allows for state-level variation in the relative growth of the $Medium$ segment, by adding interactions of 13 state dummies with $Post * Medium$ (and $Medium$) to the set of explanatory variables. The results for the coefficient on $HYV71 * Post * Medium$ show that for every outcome, the within-state correlations between the response to the credit shock and $HYV71$ are negative and statistically significant.[29]

Shocks to the $Small$ and $Medium$ industrial sectors might be correlated within districts, or even across nearby districts. The last three columns in Table 8 address this issue of spatial correlation in errors. These regressions are identical, respectively, to those shown

[28]Industrial policy statements are summarized at the Government of India website: $http://siadipp.nic.in/publicat/nip0791.htm$. There were no significant changes in the public sector policy until 1991.

[29]The estimated coefficients are smaller than those in Table 5, which suggests that part of the variation in the response to the SSI redefinition was at the state level. For instance, column (2) of Table 8 indicates that controlling for state effects, lowering $HYV71$ from the 75th to the 25th percentile raises the effect of the credit shock on the growth rate of fixed capital by about 90 percentage points, and not 135 as indicated in Table 5, column (2).

in columns (1), (2) and (4) of Table 5, except that below the usual robust standard errors (in parenthesis), I also present alternative standard errors (in brackets) calculated using the spatial GMM approach of Conley (1999). In calculating these standard errors, the error term u_{cjt} is permitted to be conditionally heteroscedastic and spatially correlated across districts as a general function of their physical distance.[30] Although these alternative standard errors are slightly higher, the coefficients on $HYV71 * Post * Medium$ remain statistically significant.

7.4 Policy Reversal

The key identifying assumption behind this paper's empirical strategy is that there was no trend in the growth of the $Medium$ factory segment, relative to the $Small$ segment, that varied across districts in a manner related to their initial HYV adoption rate. This section gives evidence against a violation of this assumption, exploiting the fact that in 2000, the SSI redefinition of 1998 was reversed by bringing the ceiling on the value of plant and machinery down from Rs. 30 million to Rs. 10 million, which is close to the old pre-1998 ceiling of Rs. 6.5 million. For now, ignoring the minor difference between the post-2000 and pre-1998 ceilings, I treat this as a full reversal, and test if even after 2000, the within-district differential in the growth of the $Medium$ and $Small$ segments continued to widen across high and low $HYV71$ districts.

To do this, I estimate a modified version of equation 18 with an additional third period of data, 2000-02. The $Post2$ dummy picks up this third period, while the $Post$ dummy is now set equal to one for both the post-1998 periods, 1998-2000 and 2000-2002.

$$\begin{aligned} X_{cjt} &= a_1 Med_c + a_2 Post_t * Med_c + a_3 Post2_t * Med_c + a_4 HYV71_j * Med_c \\ &\quad + b_1 HYV71_j * Post_t * Med_c + b_2 HYV71_j * Post2_t * Med_c \delta_{jt} + u_{cjt} \end{aligned} \tag{19}$$

A coefficient of zero on the $HYV71_j * Post2_t * Medium_c$ term (b_2) would mean that the cross-district variation in the relative growth of $Medium$ factories which emerged after 1998 continued beyond the policy reversal in 2000, indicating a violation of the identification assumption.

Table 9 presents the results from this falsification test, looking at three outcomes-average annual growth in the number of factories, total fixed capital and employment in a factory segment. The null of a zero coefficient on $HYV71 * Post2 * Medium$ can be rejected at the 1% level in each regression, which supports the identification assumption. The estimated

[30] Another recent paper which uses this approach to account for spatial dependence is Conley and Udry (2008). These standard errors use the limiting results for cross section estimation with spatial dependence in Conley (1999). Specifically, asymptotic covariance matrices for moment conditions are estimated as weighted averages of sample autocovariances, with a weighting function that is the product of one kernel in each dimension (North-South, East-West). In each dimension, the kernel starts at one and decreases linearly until it is zero at a latitudinal (or longitudinal) distance of 2^o and remains at zero for larger distances. These standard errors are robust the varying the cutoff between 1^o and 2^o. Note that India lies roughly between 75-90 degrees N and 10-30 degrees E.

coefficients on $HYV71*Post2*Medium$ are *positive* and of magnitudes similar to the negative coefficients on $HYV71*Post*Medium$, which says that the differential pattern which emerged in the 1998-2000 period essentially disappeared after 2000, when the policy change was reversed.

How long would the response to the 1998 credit shock have lasted in the absence of the 2000 reversal? This depends on how long it takes for factories to expand, and for new factories to be set up in response to changes in the supply of capital. In the absence of panel data on factories, I cannot track entry and exit, but a reasonable guess would be that in the two years following the credit shock, the response consisted mostly of expansion in existing $Medium$ factories, or the movement from *Small* to $Medium$. Had the new credit regime persisted, there might have been more of a "long-run" response, consisting of new $Medium$ factories that would otherwise have either not been set up, or set up with a smaller size.

In this context, the fact that the ceiling reversal in 2000 was partial could be useful, since the size segment ranging between Rs 6.5-10 million in plant and machinery continued under the new SSI credit regime even after 2000. Did this sub-segment of $Medium$, which I denote by $Medium_1$, continue to show a differential growth pattern across high and low $HYV71$ districts beyond 2000? I examine this below by comparing growth in *three* factory size segments- $Small$, $Medium_1$ and $Medium_2$ (Rs. 10-30 million).

$$\begin{aligned} X_{cjt} &= \sum_i (a_1^i Med_{i,c} + a_2^i Post_t * Med_{i,c} + a_3^i Post2_t * Med_{i,c} + a_4^i HYV71_j * Med_{i,c}) + \\ & \sum_i (b_1^i HYV71_j * Post_t * Med_{i,c} + b_2^i HYV71_j * Post2_t * Med_{i,c}) + \delta_{jt} + u_{cjt} \quad (20) \end{aligned}$$

where $i \in \{1, 2\}$, and the omitted factory dummy is $Small$.

OLS estimations of Equation 20 (Table 10) show that the post-2000 changes in the cross-district differential in relative growths of the Rs. 6.5-10 million and Rs. 10-30 million segments were similar. Thus, the differential growth pattern of the $Medium$ segment reverted back to its pre-1998 state in both sub-segments, suggesting that the adjustment to the SSI redefinition was over by 2000. This finding should however be interpreted with caution, since $Medium_1$ comprises just 14% of the $Medium$ size range, and it is possible that had the new SSI regime lasted beyond 2000 for the entire $Medium$ segment, much of any long-run entry response would have been outside this narrow sub-range.

Summing up, the results on the policy reversal essentially serve to dispense with concerns of a differential cross-district trend in the relative growth of the treated ($Medium$) segment. Given that the 2000 announcement amounted to a near full reversal of the 1998 SSI redefinition, these results say little about the longer-run response to the credit supply shock.

8 Interpreting the Initial HYV Adoption Effect

The large cross-district variation in the response to the SSI redefinition indicates differences in the returns to investment across districts, as predicted by the model of imperfect capital mobility. The estimated magnitude of this differential growth can be used to infer how the marginal returns to factory investment vary across districts. Equation 16 implies that the response difference between any two districts j and k,

$$[log(Med_{post,j}) - log(Med_{pre,j})] - [log(Med_{post,k}) - log(Med_{pre,k})] = \tau[log(r_j^*) - log(r_k^*)] \quad (21)$$

The intuition behind this relationship lies in the log-linearity of the assumed Cobb-Douglas production function. In logarithmic terms, given the district productivity distribution, the drop in marginal returns associated with an increase in capital stock within a district depends only on the curvature of the production function, given by the parameter $\tau = \frac{1-\beta}{1-\alpha-\beta}$, where α and β are capital and labor's shares in output, respectively, and $(1-\alpha-\beta)$ measures decreasing returns. Moreover, since the "target" rate of return (r_{ssi}^*) behind the expansion of $Medium$ factories was the same across districts, the difference in their expansion then reflects the gap in their initial rates of return.

I assume a conservative value for the extent of decreasing returns, setting $(1 - \alpha - \beta)$ to be 10 percent, and split the remaining share 1/3 to capital and 2/3 to labor ($\alpha = 0.3$ and $\beta = 0.6$).[31] Suppose districts j and k are at the 25th and 75th percentiles, respectively, of the cross-sectional distribution of initial HYV adoption. The coefficient on $HYV71*Post*Medium$ in Table 5, column (2) then indicates that in response to the credit shock, j had 1.35 points higher growth in the logarithm of fixed capital. Hence,

$$\tau[log(r_j^*) - log(r_k^*)] = 1.35 \quad (22)$$

Since $\tau = 4$ by assumption, this implies that the marginal return to investment was roughly 34% higher in the lower initial HYV adoption district j. Thus, despite the conservative assumption on decreasing returns, my results indicate a sizable gap in the marginal returns to capital across Indian districts, an inference that does not rely on any assumption on the distribution of TFP across districts.

Since initial HYV adoption is uncorrelated with recent changes in wealth or productivity, these results also suggest *persistent* differences in returns across Indian districts. Unequal early Green Revolution gains, in fact, are stronger predictors of the credit shock response than current wealth. This is shown in Table 11, which presents OLS estimates of Equation 18, when $HYV71$ is replaced by $Wealth$, the logarithm of the district's mean per capita assets in 1992. The regressions thus correspond to those in Table 5, but the districts are sorted by current wealth instead of initial HYV adoption. The coefficient on $Wealth*Post*Medium$ is negative

[31] As in Restuccia and Rogerson (2007).

in every column, which is consistent with previous results and with capital immobility, since it implies that wealthier districts responded less to the SSI credit shock. But the patterns are weaker: for instance, the estimate in column (1) implies that a 75th to 25th percentile decrease in $Wealth$ (0.7 points) is associated with a 18 percentage points higher credit shock response in fixed capital, as compared to 135 points for $HYV71$. Regressions using current wealth are subject to reverse causality concerns, since wealth could be higher because of recent productivity shocks to the manufacturing sector. Using current wealth instead of $HYV71$ would then underestimate the effect of capital immobility, which is consistent with the weaker results in Table 11.

In interpreting the coefficient on $HYV71 * Post * Medium$, however, it is important to keep in mind that in theory, the district-level variation in returns to capital, which is what the coefficient reflects, depends not just on variation in district capital supply, but also productivity a_i. If $HYV71$ is uncorrelated with long-term district productivity, then this coefficient captures purely the relationship between district assets and the returns to capital. But this may not be a realistic assumption: although initial HYV adoption was largely a function of the peculiarities of early HYV technology, it could be that early adoption disparities affected trajectories other than those of assets, such as those of public investment in agriculture, or school enrollment (Foster and Rosenzweig (1996)).

District-level data, limited as they are, suggest that early HYV adoption is correlated with characteristics other than wealth, such as the literacy rate, length of roads, irrigation and yields, even within-states (Figures 8 and 9). To the extent that these features are related to underlying, long-run determinants of productivity, these correlations suggest that it is not possible to disentangle the wealth and productivity (TFP) effects behind $HYV71$. The direction of causation is not always clear: higher yields, for instance, indicate higher agricultural productivity and hence higher labor costs to industry, but on other hand, it could be that high $HYV71$ districts have higher yields *because* they are wealthier and have invested more in agricultural improvements. The first interpretation is also inconsistent with the observation that higher $HYV71$ districts have smaller agricultural sectors. Moreover, the correlations with education and roads suggest that manufacturing TFP is *higher* in high HYV adoption districts. If so, then since high adoption districts responded less to the credit shock, the wealth effect on the district returns to capital must have dominated any TFP effect.

Nevertheless, the key implication of this paper- that there is capital immobility and that it can lead to the persistence of regional inequalities- does not depend on knowing the exact contribution of wealth to the coefficient on $HYV71 * Post * Medium$. Neither does the policy implication that more efficient financial markets will lead to greater industrial investment in the lower $HYV71$ districts, which are less industrialized and poorer.[32]

[32] That is, capital immobility does not automatically imply that there is over-investment in wealthier districts. In principle, if productivity in wealthier districts were high enough, or agglomeration economies strong enough, the response to the credit shock could have gone in the other direction. In that case, the policy implication would have been that increasing capital mobility would increase the regional disparities in industrialization.

9 Conclusion

In most developing countries, the vast majority of manufacturing employment is in small and medium establishments. The location decisions of such factories, therefore, have significant consequences for the geography of growth within these countries. This is particularly true of large, regionally diverse countries like China and India where, for a number of reasons, labor mobility is restricted. Here, regions less suited to agriculture could be ideal locations for factories that mainly require cheap labor (Foster and Rosenzweig (2004)), were it not for location-specific constraints on raw materials or capital.

This papers focussed on the role of capital constraints in the location of manufacturing investment across Indian districts, a question motivated by two observations: the persistent correlation between district wealth and investment, and heavy borrowing by firms in informal markets, which occurs in spite of an extensive bank branch network and an explicit policy mandate on lending to small firms. The problem with making an inference on capital immobility from these facts alone is that wealthier districts could be inherently more productive, and informal credit networks could be transferring capital efficiently across districts. I dealt with this causality issue through a quasi-experimental approach: if there really are differences in returns across districts, then the investment response to a nationally uniform "credit shock" will differ across districts. My finding is that there was sizable variation in the district response to a mandated credit expansion, related systematically to past agricultural shocks to district wealth, and in the direction predicted by capital immobility. Hence, certain types of poor districts have substantially high, untapped returns to factory investment.

These findings of a major capital market imperfection should give pause to discussions on the inevitability of widening regional disparities in rapidly developing countries: mobile factory capital in search of the highest returns might not necessarily flow to the already industrialized areas. My results also indicate that in India, policies focussing on bank branch expansion and directed credit to small industry may have achieved targets remarkable in their own right, but have not been able to allocate capital efficiently across regions. Probable causes, such as the incentives faced by public-sector bankers (Banerjee et al. (2004)), need to be understood better, given the potential for reducing inequality and inefficiency. Another reason for working on ways to improving capital mobility is that as long as this factor market imperfection bites, enterprise policy reforms, such as simplification of factory registration procedures, will have unequal impact across regions.

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Table 1: Summary Statistics for District Level Industrial Data

	(1) All	(2) Small	(3) Medium	(4) Large
		1994		
Number of Factories	364	316	24	23
	(585)	(505)	(49)	(57)
Workers	19903	8258	2292	9352
	(31757)	(15372)	(4567)	(17540)
Net Fixed Capital	7327	301	268	6756
	(21125)	(556)	(520)	(20811)
Gross Value of Plant and Machinery	9174	263	311	8600
	(34628)	(475)	(614)	(34401)
Output	12602	2576	1466	8559
	(21294)	(4426)	(2906)	(15678)
Value Added	2564	410	265	1944
	(5295)	(870)	(682)	(4270)
Loans	4959	348	263	4347
	(12026)	(606)	(521)	(11472)
		2000		
Number of Factories	382	317	34	30
	(650)	(532)	(71)	(62)
Workers	19151	8264	2110	8776
	(32770)	(16770)	(4755)	(16111)
Net Fixed Capital	9156	511	410	8234
	(17527)	(1031)	(896)	(16301)
Gross Value of Plant and Machinery	9637	132	332	9171
	(19237)	(278)	(687)	(18624)
Output	18553	3688	1839	13025
	(34538)	(6625)	(3858)	(26841)
Value Added	3281	478	291	2525
	(6943)	(981)	(765)	(5681)
Loans	5563	474	340	4749
	(10860)	(869)	(783)	(9888)
Initial HYV Adoption		0.102		
		(0.108)		
log(Initial HYV Adoption) [$HYV71$]		-2.73		
		(1.66)		
Per Capita Assets (in Rs 1000)		24		
		(12)		
N	271	271	271	271

Means of district totals, with standard deviations across districts in parenthesis. Statistics in column (1) include all ASI factories, while those in columns (2), (3) and (4) are for factories with gross value of plant and machinery below Rs. 6.5 million, between Rs. 6.5-30 million, and above Rs. 30 million, respectively. All values are in 1994 prices and Rs. million.

Table 2: Summary Statistics for High and Low Wealth Districts

	Low Wealth	High Wealth
(A)	All Factories	
Number of Factories	347	381
	(540)	(628)
Workers	20573	19247
	(33690)	(29856)
Net Fixed Capital	6803	7839
	(14907)	(25848)
Output	11831	13356
	(20109)	(22441)
Value Added	2571	2556
	(4886)	(5684)
Loans	5845	4092
	(15220)	(7685)
(B)	Small and Medium Factories	
Number of Factories	325	355
	(499)	(591)
Workers	10758	10348
	(19863)	(17095)
Net Fixed Capital	478	660
	(830)	(1216)
Output	3220	4847
	(5201)	(8594)
Value Added	550	791
	(986)	(1808)
Loans	526	696
	(946)	(1195)
N	135	136

Means of district totals from the Annual Survey of Industries, 1994, with standard deviations across districts in parenthesis. Panel B excludes factories with gross value of plant and machinery above Rs. 30 million. Low (High) wealth districts are those with 1992 per capita assets below rate below (above) the median value of Rs. 22,000. Fixed capital, value of plant and machinery, output, value added and loans are in 1994 prices, expressed in Rs. million.

Table 3: Summary Statistics for High and Low HYV Adoption Districts

	Low HYV	High HYV
(A)	All Factories	
Number of Factories	245	481
	(464)	(665)
Workers	14821	24873
	(28364)	(34134)
Net Fixed Capital	5293	9316
	(12715)	(26829)
Output	9842	15301
	(19813)	(22394)
Value Added	2162	2957
	(4787)	(5739)
Loans	3800	6092
	(10826)	(13034)
(B)	Small and Medium Factories	
Number of Factories	229	449
	(433)	(621)
Workers	8075	12972
	(19158)	(17530)
Net Fixed Capital	425	712
	(916)	(1144)
Output	2665	5390
	(5377)	(8346)
Value Added	513	826
	(1332)	(1570)
Loans	429	790
	(888)	(1217)
N	135	136

Means of district totals from the Annual Survey of Industries, 1994, with standard deviations across districts in parenthesis. Panel B excludes factories with gross value of plant and machinery above Rs. 30 million. Low (High) HYV districts are those with a 1971 HYV adoption rate below (above) the median value of 6.4%. Fixed capital, value of plant and machinery, output, value added and loans are in 1993 prices, expressed in Rs. million.

Table 4: Initial District HYV Adoption Rate, Per Capita Wealth and Sectoral Employment

Panel A

	Per Capita Wealth
HYV71	.097
	(.029)***
Obs.	271
R^2	.066

Panel B

	(1)	(2)	(3)	(4)
	% Employed in			
	Factories	Agriculture	Self-employment	Services
HYV71	.204	-2.193	.421	-.943
	(.077)***	(1.138)*	(.161)***	(.300)***
HYV71*Year2000	-.622	-1.513	-5.711	-4.678
	(.549)	(1.832)	(5.976)	(5.433)
Year2000	1.068	-.028	13.012	10.471
	(1.263)	(3.765)	(13.773)	(12.518)
Obs.	542	542	542	542

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. Panel A regresses the log of district per capita household assets on HYV71, the log of the district initial HYV adoption rate. Panel B regresses percentage district workforce employed in various sectors (ASI factories, agriculture, self-employment in services or manufacturing, and wage employment in services) in 1988 and 2000 on HYV71 and its interaction with Year2000, a dummy for year = 2000.

Table 5: Initial HYV Adoption Rate and the Response to the Credit Shock

	(1)	(2)	(3)	(4)
		Δ log		
	Factories	Fixed Capital	Plant & Machinery	Employment
HYV71*Post*Medium	-.275	-.928	-.834	-.373
	(.053)***	(.251)***	(.234)***	(.093)***
HYV71*Medium	.060	.174	.170	.064
	(.021)***	(.092)*	(.092)*	(.041)
Medium	.409	.549	.524	.319
	(.065)***	(.262)**	(.260)**	(.118)***
Post*Medium	-1.514	-4.003	-2.788	-1.877
	(.172)***	(.733)***	(.691)***	(.286)***
District*Period FE	Y	Y	Y	Y
Obs.	1084	1084	1084	1084
Estimation		OLS		

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. An observation is a district-period-size cell, with 271 districts, 2 periods and 2 size groups- "Small" and "Medium". The two periods are 1994 to 1998 and 1998 to 2000, the latter indicated by the "Post" dummy. The dependent variable is the per annum change in log of x plus 1, where x is # factories, value of fixed capital, value of plant & machinery or total employment in the district-period-size cell. "HYV71" is the log of district initial adoption of HYV seeds.

Table 6: Initial HYV Adoption Rate and the Loan and Output Response to the Credit Shock

	(1)	(2)	(3)	(4)
			Δ log	
	Loans	Revenue	Wages + Rent + Interest + Profit	Value Added
HYV71*Post*Medium	-.572	-.754	-.277	-.482
	(.279)**	(.272)***	(.230)	(.305)
HYV71*Medium	.055	.095	-.087	-.095
	(.101)	(.116)	(.103)	(.101)
Medium	.184	.375	.009	-.088
	(.290)	(.322)	(.279)	(.271)
Post*Medium	-2.667	-3.774	-2.293	-2.905
	(.821)***	(.808)***	(.744)***	(.880)***
District*Period FE	Y	Y	Y	Y
Obs.	1084	1084	894	943
Estimation			OLS	

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. The number of observations in columns (3) and (4) is less than 1084 because some district-year-size cells have negative value added or negative factor payments. For other outcome variables, the results presented in this and in other tables are robust to limiting the sample to 943 district-year-size cells with non-negative value added.

Table 7: Robustness Checks- Excluding Reserved Industries and Publicly Owned Establishments

	Non-reserved			Private		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log					
	Factories	Fixed Capital	Employment	Factories	Fixed Capital	Employment
HYV71*Post*Medium	-.283 (.053)***	-1.002 (.251)***	-.404 (.094)***	-.202 (.050)***	-.606 (.251)**	-.268 (.096)***
HYV71*Medium	.059 (.021)***	.179 (.092)*	.067 (.041)	.037 (.021)*	.057 (.098)	.045 (.047)
Medium	.398 (.065)***	.566 (.262)**	.331 (.118)***	.363 (.069)***	.168 (.292)	.296 (.138)**
Post*Medium	-1.550 (.174)***	-4.321 (.737)***	-2.025 (.289)***	-1.312 (.176)***	-2.766 (.772)***	-1.603 (.309)***
Dist*Period FE	Y	Y	Y	Y	Y	Y
Obs.	1084	1084	1084	1084	1084	1084
Estimation	OLS					

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. Estimates in columns (1)-(3) exclude factories in industries reserved for Small Scale Industry. Estimates in columns (4)-(6) exclude factories with government, public or joint public-private ownership.

Table 8: Robustness Checks- State-specific Responses and Spatial Clustering

	State Effects			Spatial OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log					
	Factories	Fixed Capital	Employmnt	Factories	Fixed Capital	Employmnt
HYV71*Post* Medium	-.151 (.057)***	-.637 (.277)**	-.245 (.105)**	-.275 (.053)*** [.069]	-.928 (.251)*** [.322]	-.373 (.093)*** [.115]
HYV71* Medium	.024 (.024)	.103 (.107)	.037 (.049)	.060 (.021)*** [.022]	.174 (.092)* [.093]	.064 (.041) [.041]
Medium	.350 (.077)***	.292 (.193)	.282 (.091)***	.409 (.065)*** [.074]	.549 (.262)** [.263]	.319 (.118)*** [.117]
Post*Med	-.813 (.297)***	-2.933 (1.379)**	-1.368 (.578)**	-1.514 (.172)*** [.232]	-4.003 (.733)*** [.869]	-1.877 (.286)*** [.326]
Dist*Period FE	Y	Y	Y	Y	Y	Y
State*Post* Medium	Y	Y	Y			
State*Med	Y	Y	Y			
Obs.	1084	1084	1084	1084	1084	1084
Estimation	OLS					

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. Estimates in columns (1)-(3) include interactions of state dummies with Post*Medium and Medium as controls. The second set of standard errors reported in columns (4)-(6) are adjusted for possible serial dependence based on location, using the Conley Spatial GMM estimator (Conley, 1999). Asymptotic covariance matrices for moment conditions are estimated as weighted averages of sample autocovariances. The weight for each term is the product of weight functions in each dimension that decline linearly and are zero beyond a cutoff number. The location coordinates are the latitude and longitude of a district, and the cutoff is 2 degrees.

Table 9: Differential Growth Patterns Beyond Year 2000

	(1)	(2)	(3)
		Δ log	
	Factories	Fixed Capital	Employment
HYV71*Post2*Medium	.287	.939	.397
	(.062)***	(.304)***	(.104)***
HYV71*Post*Medium	-.275	-.928	-.373
	(.053)***	(.251)***	(.093)***
HYV71*Medium	.060	.174	.064
	(.021)***	(.092)*	(.041)
Medium	.409	.549	.318
	(.065)***	(.262)**	(.118)***
Post*Medium	-1.514	-4.003	-1.877
	(.172)***	(.733)***	(.286)***
Post2*Medium	1.478	4.823	2.125
	(.202)***	(.915)***	(.334)***
District*Period FE	Y	Y	Y
Obs.	1626	1626	1626
Estimation		OLS	

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. An observation is a district-period-size cell, with 271 districts, 3 periods and 2 size groups- "Small" and "Medium". The three periods are 1994 to 1998, 1998 to 2000, and 2000 to 2002. "Post" = 1 for 1998 to 2000 *and* 2000 to 2002; "Post2" = 1 for 2000 to 2002.

Table 10: Partial Policy Reversal in 2000

	(1)	(2)	(3)
		Δ log	
	Factories	Fixed Capital	Employment
HYV71*Post2*Medium1	.315	1.093	.473
	(.059)***	(.249)***	(.101)***
HYV71*Post2*Medium2	.278	.921	.378
	(.065)***	(.291)***	(.107)***
HYV71*Post*Medium1	-.271	-1.022	-.384
	(.046)***	(.209)***	(.088)***
HYV71*Post*Medium2	-.261	-.826	-.364
	(.052)***	(.238)***	(.090)***
HYV71*Medium1	.047	.152	.043
	(.019)**	(.083)*	(.040)
HYV71*Medium2	.054	.095	.062
	(.020)***	(.088)	(.039)
District*Period FE	Y	Y	Y
Obs.	2439	2439	2439
Estimation		OLS	

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. An observation is a district-period-size cell, with 271 districts, 3 periods and 3 size groups- "Small", "Medium1" and "Medium2". The three periods are 1994 to 1998, 1998 to 2000, and 2000 to 2002. "Post" = 1 for 1998 to 2000 *and* 2000 to 2002; "Post2" = 1 for 2000 to 2002. All regressions include the variables Medium1, Medium2, Post*Medium1, Post*Medium2, Post2*Medium1 and Post2*Medium2 as controls.

Table 11: District Per Capita Wealth and the Investment Response to the Credit Shock

	(1)	(2)	(3)	(4)
	Δ log			
	Factories	Fixed Capital	Plant & Machinery	Employment
Wealth*Post*Medium	-.328	-.248	-.366	-.363
	(.182)*	(.758)	(.724)	(.311)
Wealth*Medium	.116	.003	.026	.117
	(.052)**	(.219)	(.217)	(.091)
Medium	-.122	.029	-.056	-.228
	(.165)	(.706)	(.701)	(.293)
Post*Medium	.300	-.522	.779	.333
	(.568)	(2.403)	(2.310)	(.985)
District*Period FE	Y	Y	Y	Y
Obs.	1084	1084	1084	1084
Estimation	OLS			

Notes: Robust standard errors in parenthesis. *** indicates 1% , ** 5% and * 10% significance level. An observation is a district-period-size cell, with 271 districts, 2 periods and 2 size groups- "Small" and "Medium". The two periods are 1994 to 1998 and 1998 to 2000, the latter indicated by the "Post" dummy. The dependent variable is the per annum change in log of x plus 1, where x is # factories, value of fixed capital, value of plant & machinery or total employment in the district-period-size cell. "Wealth" is the log of district mean per capita household assets.

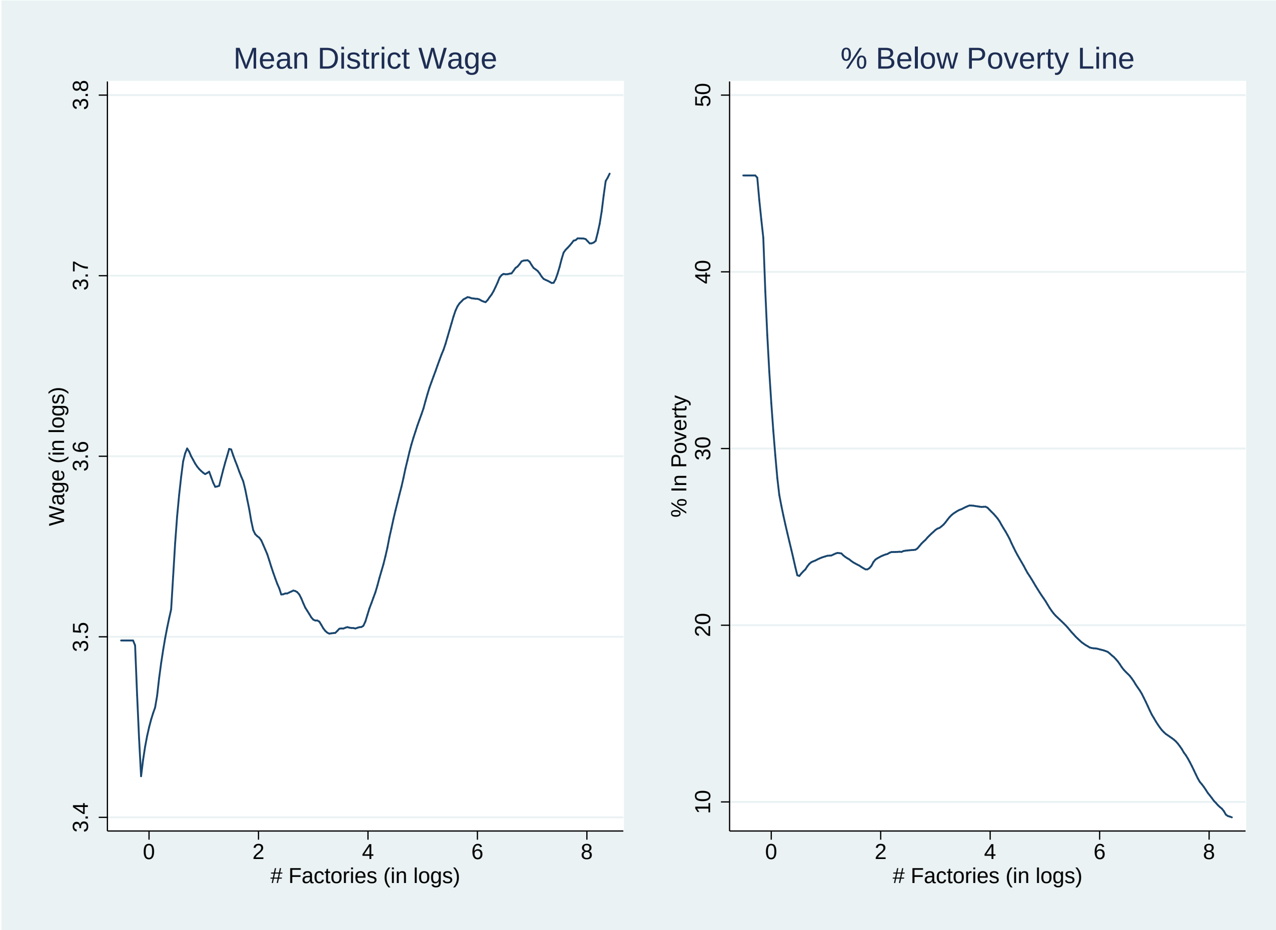

Figure 1: Industrialization, Wages and Poverty Rates Across Indian Districts in 2000 (Non-parametric Kernel Regressions based on data from Annual Survey of Industries and National Sample Survey of Employment and Unemployment)

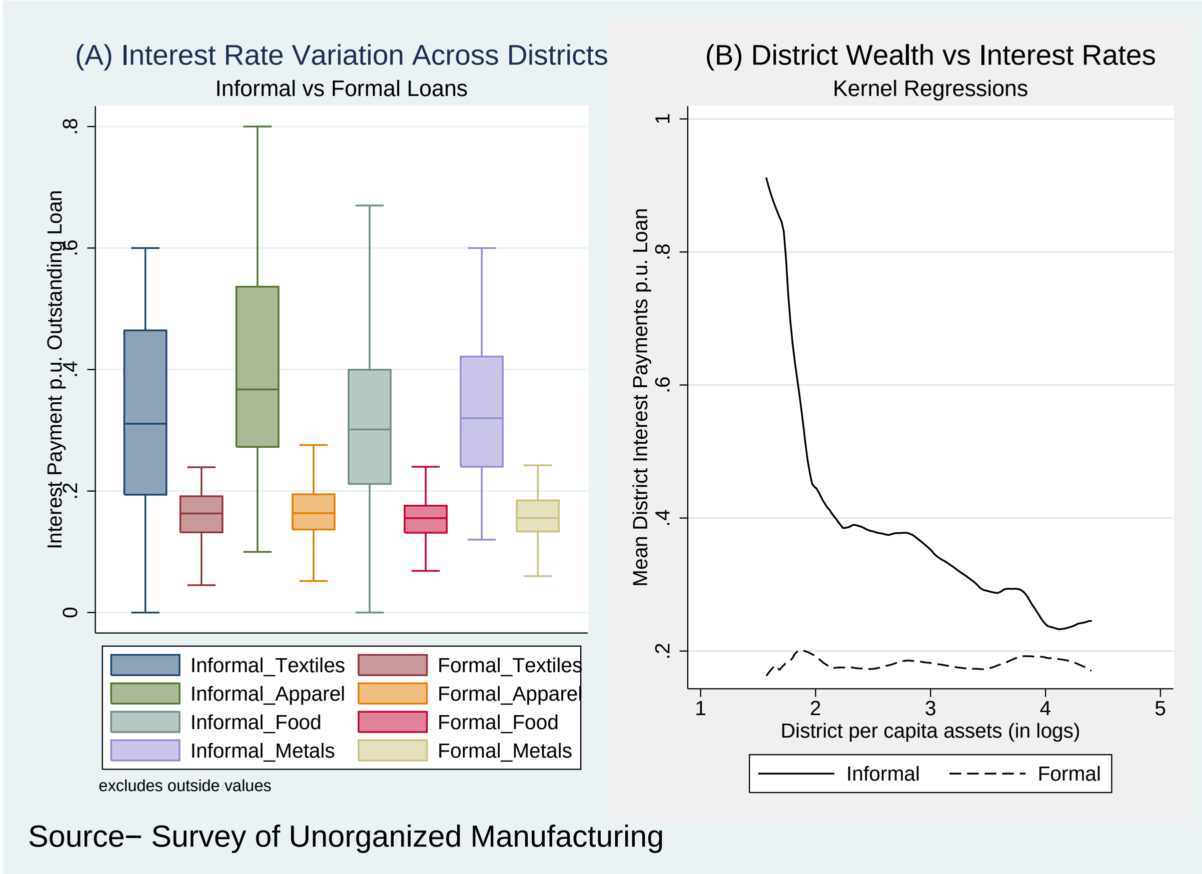

Figure 2: Formal and Informal Interest Rates Across India. (Panel A plots the 25-75 percentile range in the ratio of interest payment to loan amount for formal and informal loans in Textiles, Apparel, Food Products and Metal Products. Panel B plots non-parametric (Kernel) regressions of district mean interest rates on wealth.)

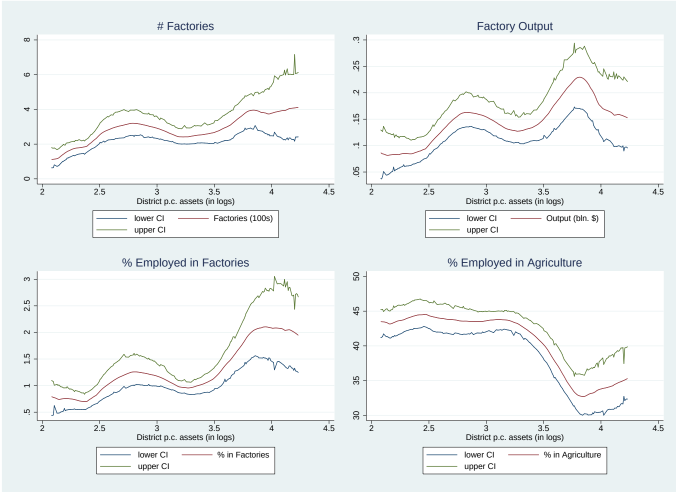

Figure 3: District Wealth vs the Factory and Agricultural Sectors in 1988 (Kernel Regression with 90% Confidence Interval)

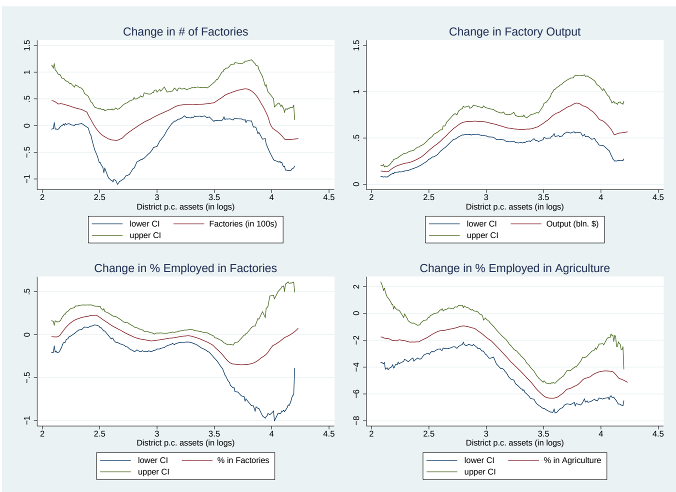

Figure 4: District Wealth vs Change in the Factory and Agricultural Sectors, 1988-2000 (Kernel Regression with 90% Confidence Interval)

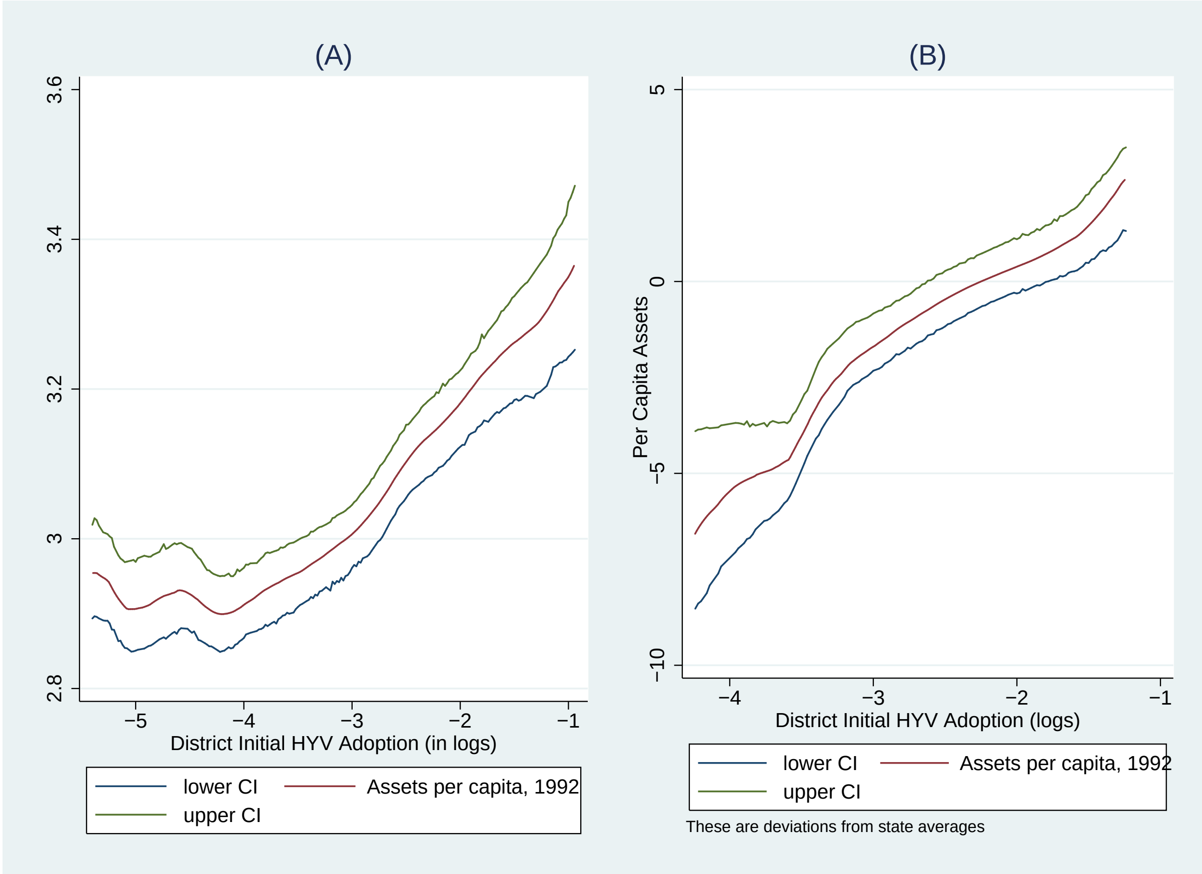

Figure 5: District Initial HYV Adoption vs Per Capita Wealth in 1992 (Kernel Regression with 90% Confidence Interval)

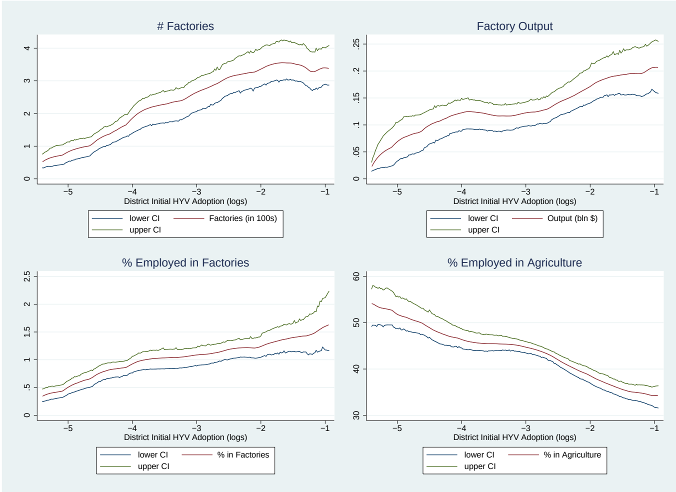

Figure 6: Initial HYV Adoption vs the Factory and Agricultural Sectors in 1988 (Kernel Regression with 90% Confidence Interval)

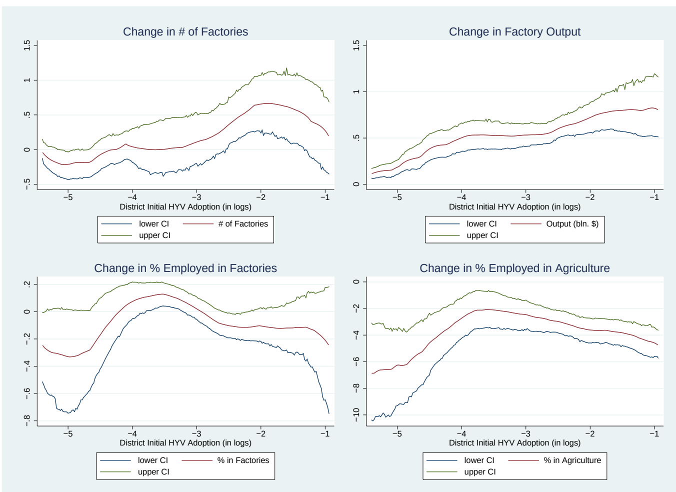

Figure 7: Initial HYV Adoption vs Change in the Factory and Agricultural Sectors, 1988 to 2000 (Kernel Regression with 90% Confidence Interval)

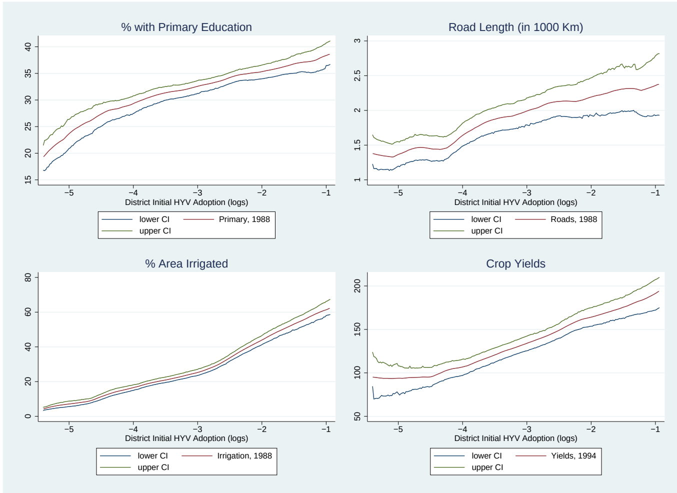

Figure 8: Initial HYV Adoption vs Literacy, Roads, Yields & Irrigation (Kernel Regression with 90% Confidence Interval)

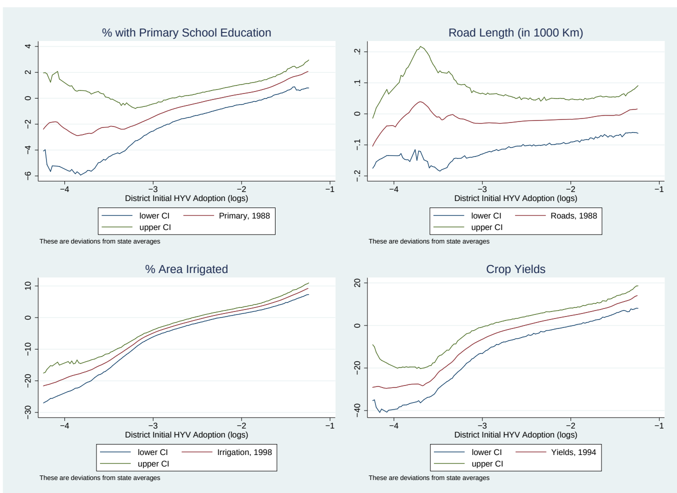

Figure 9: Initial HYV Adoption vs Literacy, Roads, Yields & Irrigation, Within-state (Kernel Regression with 90% Confidence Interval. The variables are measured as deviations from their respective state-level means.)

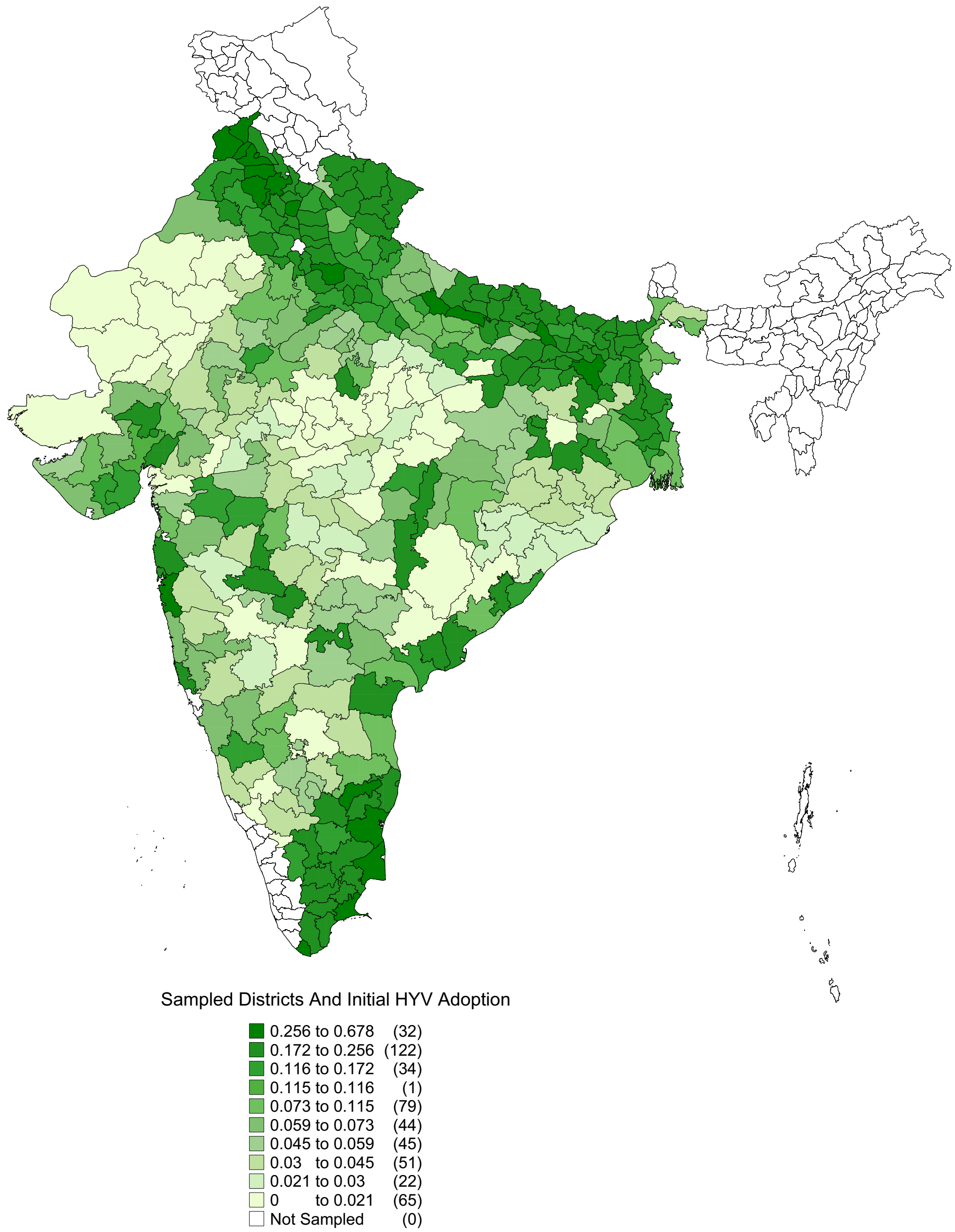

Figure 10: Initial HYV Adoption in Indian Districts (% Cultivated Area)