Capital Quality, Productivity, and Financial Constraints: Evidence from India*

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Abstract

This paper provides novel evidence that reduced financial constraints increase physical capital quality and, consequently, productivity. We use a project-level investment dataset from India, CapEx, with data on project cost, capacity added to the firm, and investment's product category. We measure physical capital quality using Unit Investment Cost (UIC), defined as the project cost divided by the additional capacity. We find UIC displays significant variation across firms and is substantially associated with productivity and output quality. However, higher-quality physical capital is more expensive, and without sufficient internal funds, firms cannot invest in them. We study a policy, the establishment of Debt Recovery Tribunals (DRT), which has generated staggered variation in access to external debt financing across different Indian states. We find that firms in treated states borrowed and invested more with all the increased investment coming from an increase in UIC and not from increased additional capacity. Furthermore, treated firms increased productivity and output quality, consistent with the hypothesis that a higher UIC induced by greater access to finance increased firm productivity and output quality. The effect of DRTs establishment is stronger in firms that rely more on external financing and industries with more scope for quality differentiation, a result which further supports this hypothesis. Available evidence suggests that other channels do not completely explain the increased productivity and output quality. Overall, this paper finds physical capital quality is an important determinant of productivity and output quality, and a firm's choice of physical capital quality depends on the availability of financing.

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1 Introduction

An extensive literature has documented that financial constraints reduce investment in physical capital – machines, buildings, and land. However, there is less attention on how financial constraints affect the firms' *quality* of physical capital. High-quality physical capital is more expensive and needs higher upfront payment. Thus, a financially constrained firm might optimally invest in lower-quality physical capital. However, physical capital with lower quality is more likely to have less cutting-edge technology, which might hamper productivity growth at the firm level and, consequently, on the whole economy. Because productivity is key to understanding differences in economic activity across countries and over time, evidence of such a link would demonstrate an important channel through which financial constraints can impact the real economy beyond the effect of reduced investment.

In this paper, we first look to confirm that the quality of physical capital does matter for productivity, and then, we look to see how financial constraints affect the quality of physical capital and consequently productivity. We use a unique dataset from India to measure physical-capital quality and document physical-capital-quality correlations with different performance measures that include productivity and product quality. Then, we exploit a policy experiment that generates staggered variation in access to external debt financing across different Indian states between 1995 and 2000. We study how the policy affected physical capital quality and productivity. A stylized model of financially constrained firms with endogenous capital-quality choice explains our findings.

The main challenge in studying these questions is the lack of detailed data on physical-capital quality used by firms for a large cross-section of firms over time. Not only are such data not typically available, but we also need detailed data on product prices and quantities sold by firms to further understand how capital quality affects firm productivity, which we measure as Total Factor Productivity (TFP).[1] In this paper, we assemble a unique dataset that contains such information by merging two datasets CapEx and Prowess, both collected by the Center for Monitoring Indian Economy (CMIE) in India. CapEx is a unique dataset that includes detailed information about firm-level investment projects, including project cost – machines, buildings, and land. However, what makes this dataset unique is that we observe the additional physical capacity added to the firm (e.g., 1.8 tonnes/day) and

[1] Data on the price and quantity of products sold by firms are critical for understanding why the quality of physical capital matters for firms.

the output of the investment project at the product level (e.g., iron ore). Prowess includes detailed data on unit prices and physical quantities of products sold by firms in addition to the balance-sheet and income-statement data. This permits us also to study how the quality of physical capital affects the quality of output produced.

We measure physical-capital quality using Unit Investment Cost (UIC), defined as the project cost divided by the additional capacity added to the firm. Firms invest in creating production capacity, and UIC captures the cost required for a firm to create the capacity to produce one unit of output. In other words, UIC is the unit price of physical capital.[2] Higher UIC capital is more expensive; thus, it is likely to have more embodied technology, which may increase firm performance in several ways. First, it might increase firm TFP. Second, it might produce higher-quality output. Third, a higher UIC capital good might be more durable, and thus, it may lower future repair and maintenance costs or depreciate at a slower rate.

We begin by documenting two descriptive findings: (1) UIC shows significant variation across firms in the same year and (2) UIC shows a high level of persistence within the same firm over time (conditional on fixing investment project' product category). On average, the ratio of the 75th to 25th percentile of the UIC is 5.24, which is substantial. In other words, the dollar value of an investment for one firm might be 5.24 times higher than another firm in the same year and product category when both have the same added production capacity. Second, within a firm, UIC is persistent over time. These findings suggest a potential role for physical-capital in explaining TFP, and they confirm two widely documented empirical regularities in firm performance studies – large cross-sectional differences and high persistence levels.

Next, we show UIC is positively correlated with TFP. We find that UIC is positively correlated with revenue-based TFP (or TFPR, for short), which measures revenue for a given set of inputs (material input, labor, and physical capital). TFPR captures technical efficiency, output quality, and markups. Using product-level output prices, we can further study the correlation of UIC with a measure of technical efficiency: quantity-based TFP (or TFPQ, for short). TFPQ measures physical quantity of output for a given set of inputs (material input, labor, and physical capital). Moving from the 25th to the 75th percentile

[2]Unit price has been used to measure input quality before. For example, Kugler and Verhoogen (2012) use the unit price of material input to measure the quality of material input.

of UIC is associated with an 18.6% and 8.1% increase in TFPR and TFPQ, respectively.

What drives the positive correlation of UIC with firm TFPR? TFPR is equal to revenue minus a weighted average cost of physical capital, labor, and material input. A higher UIC might increase TFPR either by increasing revenue (determined by output price and output quality) or by decreasing costs.[3,4] We find higher UIC is indeed positively correlated with revenue and negatively correlated with both material input and labor. We also find UIC is positively correlated with both output price and output quality.[5]

High UIC physical capital is positively correlated with both TFP and output quality, but what about durability? We show that UIC is negatively correlated with repair and maintenance costs. The negative correlation suggests that higher UIC capital is more durable.

We show a particular mechanism in which a higher UIC enables firms to produce higher output quality can simultaneously explain the positive correlation of UIC with revenue, output price, output quality, and TFPR. Improvements in output quality are particularly important in developing countries and are believed to be one of the key growth drivers.[6] This hypothesis implies the benefits of having higher UIC physical capital will be higher in industries with more scope for quality differentiation.[7] To test that hypothesis, we interact output quality, price, and TFPR with a measure of scope for quality differentiation and find that in industries with higher scope for quality differentiation, the benefits of using higher UIC are higher.

We next show the above findings can be rationalized in a model. We develop a stylized static model of firms facing constant elasticity of substitution (CES) demand to show that

[3]Purchasing physical-capital is a cost to the firm. Thus, the cost of physical capital goes up. However, a higher UIC might lower other costs, such as labor.

[4]Assuming a Constant Elasticity of Substitution (CES) demand system, sales share can be decomposed into price and a residual component interpreted as output quality. For more details, see subsection 3.3.2

[5]For studying the price and quality, we used a unique feature of the data. We can directly observe output prices and sales for a subset of investment projects matched to the corresponding output product. This mapping is important because a well-known problem in studying multi-product firms is the lack of direct mapping between inputs and outputs. Our dataset is unique because we observe a direct link between an input (physical-capital) and output price and sales in a large sample of multi-product firms. The positive correlation of UIC and output price and quality is consistent with that of earlier literature (see, e.g., Kugler and Verhoogen (2012)).

[6]Refer to quality-ladder literature originated in Grossman and Helpman (1991). Furthermore, Atkin, Khandelwal, and Osman (2017) and Bastos, Silva, and Verhoogen (2018) note that as global incomes rise, access to wealthier and quality-sensitive markets increases output quality returns.

[7]This mechanism is similar to the mechanism highlighted in Kugler and Verhoogen (2012), who find that using higher-quality input is associated with producing higher-quality output.

this simple model can explain the main results. In the model, firms need to invest in creating production capacity, and they choose both UIC and the dollar value of the investment. A higher UIC investment increases output quality and reduces the cost of production.[8] Firms can invest only by borrowing, and they are heterogeneous in how much they can borrow.[9] Despite its simplicity, the model can explain all findings discussed so far. Furthermore, it provides a theoretically consistent framework for our empirical findings relating financial constraints to the choice of UIC, which we explain next.

Considering that a higher quality of physical capital increases TFP, why doesn't every firm invest in the highest quality? We provide one potential answer: financial constraints prevent firms from selecting the highest net present value investment opportunities. We use a quasi-natural experiment, the staggered introduction of Debt Recovery Tribunals (DRT) from 1995 to 2000 across different states in India as an exogenous source of increase in the availability of debt-financing. DRTs were specialized courts designed to improve the enforcement of debt recovery. The policy was designed to make the recovery rate of loans higher for the creditors. These policies are important and prevalent around the world, especially so in developing countries.[10] The law was effective in increasing the banks' willingness to lend. This has been documented in several research articles, including Visaria (2009), von Lilienfeld-Toal, Mookherjee, and Visaria (2012), Gopalan, Mukherjee, and Singh (2016). Consistent with that prior literature, we show firms indeed increase borrowing and the total dollar value of the investment.

We show treated firms increased investment *only by increasing UIC* and not by increasing capacity. Although, theoretically, an increase in investment can reflect an increase in either margin, the finding that firms only increase investment by increasing UIC further highlights the importance of UIC in a firm's investment decisions. We show treated firms increase TFPR, TFPQ, output price, and output quality relative to the control group. Furthermore, we find the increment in TFPR, output price, and output quality is more substantial in industries with a higher scope for quality differentiation. These findings provide evidence

[8]Cost of production here refers to the cost of producing output without considering the cost of physical capital. Of course, the cost of physical-capital enters the firm's optimization problem, too.

[9]Heterogeneity in a firm's ability to borrow is an important determinant of investment decisions, as highlighted by the extensive studies in the financial economics literature.

[10]The policy that we study is an example of "creditor protection" policies. A few examples of such policies that have been studied in developing countries include China (Li and Ponticelli (2020)), Brazil (Ponticelli and Alencar (2016)), 12 emerging markets around the world (Calomiris, Larrain, Liberti, and Sturgess (2017)).

that a higher UIC induced by greater access to finance increases firm productivity and output quality.

We further exploit cross-sectional heterogeneity across firms and industries to clarify whether our results are consistent with the credit-market-frictions channel. If financial constraints prevent firms from investing in higher UIC, we expect the UIC and TFP results to be stronger for ex-ante, more constrained firms. We find this result when we interact DRT establishment with four measures of financial constraints: age, size, industry leverage, and Rajan and Zingales (1998) measure of external financial dependence.

The establishment of DRTs should affect firm performance through investment in higher UIC capital. However, it could also affect firm-level outcomes through other channels. Studying the alternative explanations serves two purposes: first, it helps identify the economic mechanism through which DRT affected TFP. Second, we find that physical-capital quality is the most plausible explanation. This finding complements the evidence provided in the first part of the paper that capital quality affects TFP. We perform several tests to investigate the relevance of other potential explanations.

First, we directly test for three specific mechanisms: increased R&D, increased training of employees, and increased intangible investment. We find that-DRT induced-changes in all three variables are neither economically nor statistically significant. Second, we focus on the sub-sample of multi-product firms. We show that the change in treated firms' price, output quality, and sales share is neither economically nor statistically significant for products that the firm did not invest in. Any explanation for our findings must explain why price, quality, and sales share increased and why that is only so for product categories that the firms invested in. Third, the TFP, price, output-quality, and sales-share results are stronger for industries with higher scope for quality differentiation. Thus, any potential explanation should be stronger in these industries, as well. In all the alternative explanations discussed so far, the coefficient of scope for quality differentiation is neither economically nor statistically significant, which provides further evidence consistent with our explanation.

Fourth, UIC is the unit price of physical capital. Thus, it depends on the pricing decision of the sellers of physical capital. If sellers of physical capital charge higher prices from unconstrained firms, we will see a higher UIC for unconstrained firms that has nothing to do with their obtaining higher-quality physical capital. In this case, we would expect UIC to increase more in industries with less competition in the physical-capital seller market.

We find that the interactions with several measures of market power in the physical-capital seller market are neither statistically nor economically significant.

Lastly, the results could be driven by changes in other state-level outcomes. For instance, the DRT establishment could have led to an increased value of land in treated states. The increased value of land might have made an investment in that state more expensive. Thus, an increased UIC for firms in treated states might be unrelated to these firms' acquiring more productive physical capital. To address this concern, we focus on a sub-sample of projects in which the project location is not treated. We find similar results in this sub-sample, as well. Thus, overall, the evidence suggests that the establishment of DRTs increased TFP through investment in higher UIC physical capital.

We conclude by summarizing the key findings of the paper in Figure 1. Panel A of Figure 1 shows UIC varies significantly across firms within the same year (conditional on investing in narrowly defined product categories). On average, the ratio of the 75th to 25th percentile is 5.24, which is quite substantial. Panel B shows UIC is positively correlated with TFPR. This finding is inconsistent with most models used in the literature, which assume the dollar value of physical capital is sufficient for understanding the contribution of physical capital to output. The figure suggests that UIC is important in explaining differences in TFPR. Panel C shows UIC is positively correlated with output quality, suggesting that higher UIC enables the production of higher-quality goods. Panel D shows UIC is positively correlated with size. Larger firms are known to be less financially constrained. Thus, the figure suggests that more financially constrained firms use lower-quality physical capital.

1.1 Related Literature

This article contributes to several strands of literature. It contributes to the extensive literature on the determinants of the large TFP differences across firms, and more specifically, the explanations that focus on the input-side (for a review of productivity literature, see Syverson (2011) and Verhoogen (2020)). The empirical literature has mostly focused on the role of material inputs (both the quality of material inputs (i.e., Kugler and Verhoogen (2012)) and access to varieties of material input (i.e., Goldberg, Khandelwal, Pavcnik, and Topalova (2010b))), labor, and access to financial capital, amongst other input-side explanations of firm performance. However, our paper focuses on how the quality of physical capital af-

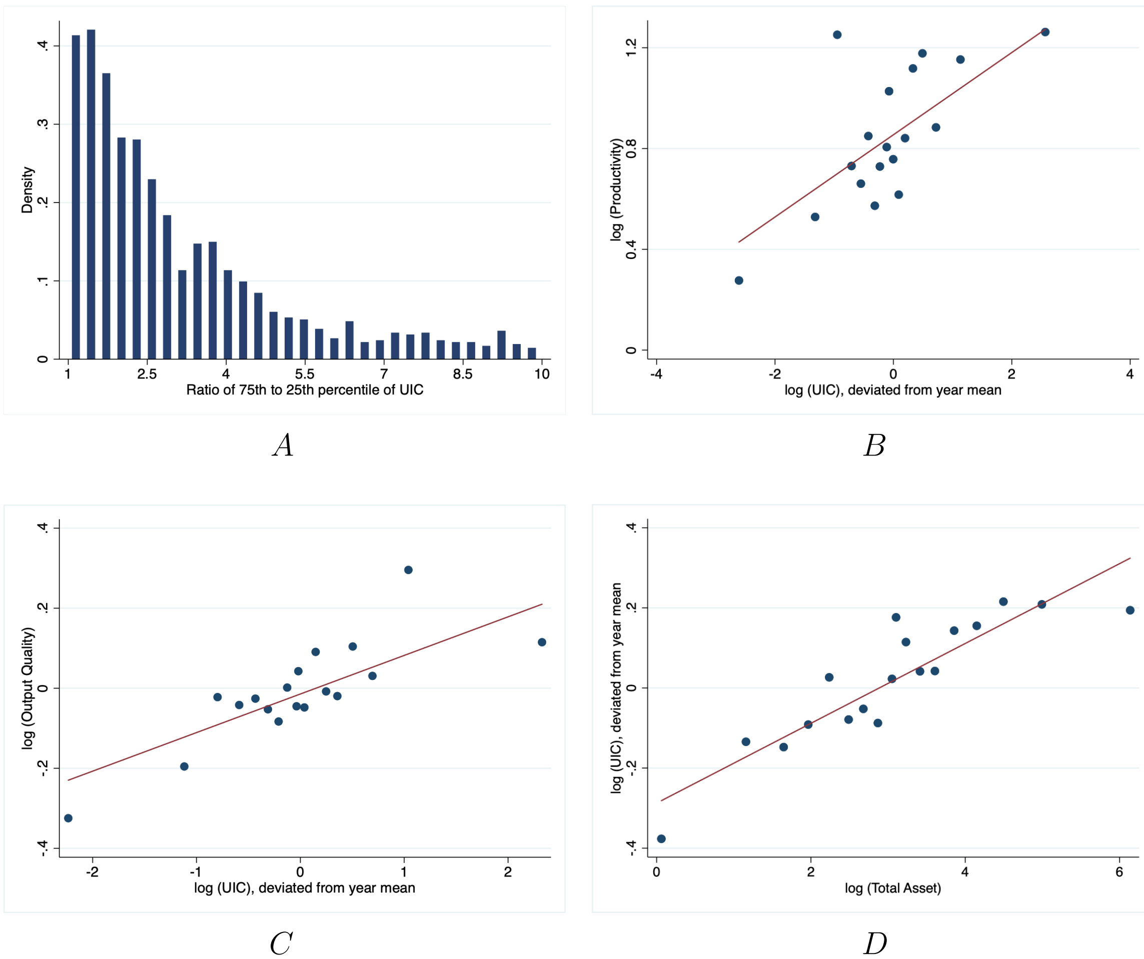

Figure 1: Panel A plots the histogram of the ratio of the 75th to the 25th percentile of UIC (within a narrowly defined product category and in a year). Outliers above the 90th percentile are trimmed. Panel B is the binscatter plot of UIC and firm productivity measured by TFPR. Panel C is the binscatter plot of UIC and output quality. Panel D is the binscatter plot of logged value of total assets and UIC.

fects firm performance (such as productivity), which remains an understudied topic, despite its potential significance.[11] Our paper contributes to this literature by providing evidence that physical capital have substantial differences in qualities, and the quality differences are important in explaining firm performance, such as TFP.

This paper also relates to the substantial literature that studies the effects of financial constraints on investment. A major challenge is how to measure financial constraints (see i.e., Fazzari, Hubbard, and Petersen (1988), Kaplan and Zingales (2000), Rauh (2006), Whited and Wu (2006), Hadlock and Pierce (2010), Farre-Mensa and Ljungqvist (2016)). The literature studies how different measures of financial constraints affect the dollar value of investments. However, what firms invest in has received much less attention. This is important because it helps our understanding of why financial constraints are important for investments. The findings in this paper suggest that financially constrained firms create as much capacity as unconstrained firms. The unconstrained ones, however, purchase higher quality capital.

This paper contributes to the literature studying the relationship between financial and economic development and the role of legal changes in promoting financial development (for a survey, see Levine (2005)). In their seminal work, King and Levine (1993) document that financial development is correlated with both increased capital accumulation and productivity across countries. We show that financial development can increase capital accumulation and productivity through investment in higher-quality physical capital. This is important because an ongoing debate in economic growth over whether factor accumulation or productivity growth contributes to growth (which we cover in more detail below) and how financial development affects them. Our results highlight the importance of financial development on a joint explanation: capital quality increases both the value of physical capital and TFP.

This paper is related to how laws and, in particular, creditor protection laws affect economic growth (see, i.e., King and Levine (1993), La Porta, Lopez-de Silanes, Shleifer, and Vishny (1997), and La Porta, Lopez-de Silanes, Shleifer, and Vishny (1998)). The particular

[11] Note two exceptions: First, a particular type of physical capital, Information Technology (IT), has been widely studied. Although IT has been an important driver of increased firm performance over the past few decades, the role of heterogeneity in physical capital, in general, is not well known. Second, the role of heterogeneous physical capital has been studied extensively in the agricultural sector. However, the economics of manufacturing is very different from the agricultural sector. In addition, manufacturing firms are crucial for economic growth (see Tybout (2000) and Hsieh and Olken (2014)).

policy that we study is an example of "creditor-protection" policies. These policies are important and prevalent around the world, especially in developing countries. These policies have been studied in China (Li and Ponticelli (2020)) and, Brazil (Ponticelli and Alencar (2016)), as well as 12 emerging markets around the world (Calomiris et al. (2017)). Our paper contributes to this literature by showing the policy is important in understanding the quality of capital. This paper is also related to Benmelech and Bergman (2011), who find that creditor-protection laws affect the vintage of capital chosen by airline companies. This paper complements theirs by providing evidence that these laws are important for capital quality, output quality, and TFP in a large set of industries, not just airline companies.

This paper also contributes to the growth accounting literature that argues for the importance of adjusting for the quality of physical capital. Whether growth happens because of factor accumulation or productivity growth has important policy implications (see, i.e., Hall and Jones (1999). Two prominent articles provide different explanations for the spectacular growth of Singapore, Hong Kong, Taiwan, and South Korea during 1966-1990. Young (1995) argues for the role of factor accumulation, whereas Hsieh (2002) argues for the role of TFP growth.). Greenwood, Hercowitz, and Krusell (1997) and Hulten (1992) consider capital-embodied technological as a from of physical capital quality, and they find that once capital-embodied technological growth is properly accounted for, capital accumulation can explain a large portion of growth. However, the growth accounting literature is mostly interested in cross-country and within-country time-series patterns of capital-embodied technological growth. We contribute to this literature by providing reduced-form evidence that quality differences in capital substantially affect TFP. Due to the detailed data available at the investment projects, we can use product categories and time fixed effects to control for unobservables.

The rest of this article is organized as follows. Section 2 describes the datasets used and provides summary statistics. Section 3 discusses measuring physical-capital quality (UIC), documents the substantial cross-sectional variation and firm-level persistence in UIC, and documents the correlation of UIC with firm outcomes. Section 4 develops a stylized model of a firm's UIC choices in the presence of financial constraints. Section 5 describes the quasi-natural experiment that improved the enforcement of debt contracts, as well as its effects on UIC and firm outcomes. Section 6 studies other mechanisms that could explain our empirical findings. Finally, section 7 concludes.

2 Data

We construct a unique dataset that combines information about investment projects of firms with balance sheet data and data on product prices and quantities sold by the firms. In this section, we describe the two main datasets used in the paper and provide summary statistics for the main variables.

2.1 CapEx dataset

We use the CapEx dataset to obtain detailed data on firm-level investment projects. This dataset is provided by the Center for Monitoring the Indian Economy (CMIE),[12] and it provides data on planned capital expenditures at the project level. The CapEx database serves as a source for tracking investment projects in the annual "Economic Review" report published by the Indian central bank - the Reserve Bank of India (RBI). All projects announced by private and public firms and government entities that cost more than 10 million Indian rupees ($\approx$ 0.25 million USD) are recorded in the database. The dataset includes information on real investments (as opposed to financial investments) that involve capacity expansion. The dataset covers projects announced from 1995 to 2020 and has overall 35,000 different completed projects. The dataset covers a wide range of projects in different industries and states in India. These projects are large and a significant part of the firm's capital expenditure. Depending on the year, these projects constitute about 80% to 96% of firm-level annual capital expenditure (calculated using changes in Property, Plant, and Equipment (PPE) plus depreciation) for the subset of firms that have at least one project in CapEx.

We observe three pieces of information that are critical for this study, and to the best of our knowledge, are unique to this dataset. First, the dataset includes information about the project cost (i.e., a project producing iron ore that costs 1.8 million USD and creates a capacity of 1.8 tonnes/day). Note that here project cost[13] refers to the ex-ante costs paid

[12]CMIE is a private company that collects information about Indian firms. The CMIE collects the Prowess dataset as well. Prowess is widely used in economics and finance academic articles. Similar to the Compustat database in the US, Prowess sources its data from publicly available annual reports and other disclosures by the firm.

[13]According to the data provider, project cost includes the sum of the costs paid by the firm for the following five categories: (i) purchasing machinery and equipment, (ii) purchasing land, (iii) purchasing equipment for building plants, (iv) payment to labor needed for installing machinery and building plants, and (v) purchasing the necessary licenses.

by the firm to purchase machines, buildings, and equipment for the production of goods. It does not include costs paid by the firm during the production of goods, such as material input. Second, we can observe the firm's product due to the investment project (iron ore in this example).

Third, and perhaps most important, we observe the additional capacity added to the firm because of the investment project (1.8 tonnes/day in this example). This variable is not available in other datasets[14] and is the key to the definition of UIC. These data are collected through different methods, including the company's announcements about investment projects. Such announcements are not unique to India and happen in the US, as well. For instance, Bloomberg[15] reports "Moderna Inc, a biotechnology company pioneering messenger RNA (mRNA) therapeutics and vaccines, announced that it is making new capital investments to increase capacity, which it expects will increase global 2022 capacity to approximately 1.4 billion doses of COVID-19 vaccine." In Appendix A, we provide further details about the data and how they are collected.

We take the following steps to clean the data. We limit the sample to projects completed from 1995 to 2003. Furthermore, we exclude projects undertaken by the state or federal governments. In addition, we assume firms invest the total project cost equally over the life of a project. For instance, if a project takes two years to complete, we assume the firm invests half of the project cost each year.

2.2 Prowess dataset

We obtain firm-level financial data from the Prowess dataset, also maintained by the CMIE.[16] Prowess has annual financial data for listed and unlisted Indian firms starting from 1989 for a wide range of firms in different industries. The firms in the dataset cover between 60% to 70% of the economic activity in the organized industrial sector that refers to registered companies that submit financial statements in India, which is quite significant.[17]

[14]To the best of our knowledge, this dataset is the only one that collects such data for a large set of firms.

[15]Please refer to https://www.bloomberg.com/press-releases/2021-02-24/moderna-announces-additional-capital-investments-to-increase-global-manufacturing-capacity-for-covid-19-vaccine for more details.

[16]The Prowess dataset has been used previously. See, for instance, Vig (2013), Gopalan et al. (2016), Goldberg, Khandelwal, Pavcnik, and Topalova (2010a) and Goldberg et al. (2010b).

[17]The firms in the Prowess sample account for 75% of corporate taxes and 95% of excise duty collected by the Government of India. Please refer to Alfaro and Chari (2010) and Goldberg et al. (2010a) for more

Prowess is unique relative to other firm-level financial datasets because it also provides data on the price and quantity of products sold by firms in narrowly defined product categories.[18] Prowess can collect such data because Indian firms are required by the 1956 Companies Act to disclose product-level information in their annual reports. CMIE uses an internal product classification that is based on the National Industry Classification (NIC) schedules. Overall, 2,918 products are linked to 292 four-digit NIC (based on 1998 classification) industries across the 60 sectors (two-digit NIC codes).

We take the following steps to clean the data. From the sample of all firms in the Prowess sample between 1994 to 2003, we exclude all financial firms (NIC code: 641-663), firms owned by central and state governments, firms with less than two years of data with positive values of total assets and PPE, firms with leverage more than one, and observations whose ratio of investment to lagged total assets is greater than 1. To mitigate outliers, we require that the firm's capital and sales be at least 1 million Indian rupees (around 0.025 million USD) in the previous year. The financial year in India starts on April 1 and ends on March 31. We make necessary adjustments to the project announcement dates to reflect this in our analysis. We use the common company identifier provided by the CMIE to merge CapEx with the Prowess dataset.

The final sample includes around 500 firms and 2,700 firm-year observations. These firms completed about 3,800 projects in approximately 400 different product categories over the entire sample period. All variables are adjusted for inflation using the Wholesale Price Index (WPI) for 2019 and converted to USD using the RBI's reported exchange rate.

Panels A and B of Table 1 contain summary statistics for the companies and projects used in this study, respectively. The mean and median firm size, measured by total assets, are 703 and 60.2 million USD, respectively. The mean and median of physical capital, measured by PPE, are 276 and 20.6 million USD, respectively. In Panel B, we provide the summary statistics for the sample of projects. The mean (median) project cost is about 78 (7.5) million USD. The median duration of a project, the period from project announcement

information.

[18] The Prowess dataset is the only dataset in India that records detailed annual information on firms' product-mix. Goldberg et al. (2010a) reports that "product-level data are available for 85% of the firms; this accounts for more than 90% of output and exports of the firms in Prowess. More importantly, the product-level information and overall output are in separate modules of the Prowess database which enables us to cross-check the consistency of the data. We show that the total product-level sales account for 92% of the (independently) reported output of the firm."

date to project completion date, is four months. The median of a firm's total project cost to its total asset, PPE, and capital expenditure is about 13%, 29%, and 71%, respectively. Furthermore, nearly 85% of all projects are completed in less than a year.

2.3 Cross-Validation of CapEx using the Prowess Dataset

In Appendix B, we provide several pieces of evidence to validate the variables reported in CapEx by using the Prowess dataset. Firms are not required by law to disclose project details. Thus, self-reporting might raise concerns about the accuracy of the data collected in the CapEx dataset. However, the data are unlikely to be inaccurate. First, the Indian central bank uses CapEx for tracking investments in India. Second, several tests further validate the accuracy of the data. CapEx has been used in a few other research articles, including Alok, Ayyagari, and Karolyi (2020) and Bahal, Raissi, and Tulin (2018). However, we are not aware of an analysis that checks the accuracy of the data reported in CapEx. In the Appendix B, we conduct several tests and compare the variables reported in CapEx with their counterparts reported in the Prowess dataset, the widely used dataset to study Indian firms. In particular, we show total project cost closely follows its firm-level balance-sheet counterpart (changes in PPE plus depreciation) both in the time series and cross section. Furthermore, we cross-check the capacity variable in the Prowess dataset (for a subset of firm-products that this variable is reported in Prowess) with the variable from CapEx and find that these two variables are consistent. Finally, we show the additional capacity variable in the CapEx dataset is consistent with the sales-quantity variable reported in the Prowess dataset as well.

3 Quality of Physical Capital

3.1 Measurement and Interpretation of UIC

We use Unit Investment Cost (UIC) to measure physical-capital quality:

$$\text{UIC} = \frac{\text{Project Cost}}{\text{Production Capacity Added to the Firm}} \tag{1}$$

Variables	Number	Mean	Median	SD
Panel A: Firm Summary Statistics				
Asset (Million USD)	2,722	703.1	60.62	2,661
PPE (Million USD)	2,722	276.2	20.62	1,162
Wage Bill (Million USD)	2,722	35.12	2.691	125.9
R&D (Million USD)	1,837	1.909	0.217	6.113
Training Expenditure (Million USD)	1,036	0.904	0.144	1.634
Intangible Investment (Million USD)	1,789	2.819	0.311	9.107
Panel B: Project Summary Statistics				
Project Cost (Million USD)	3,851	78.12	7.512	327.1
Duration	3,851	0.485	0.421	0.371
Sum Project Cost/Total Asset	2,722	0.171	0.132	0.184
Sum Project Cost/PPE	2,722	0.351	0.292	0.312
Sum Project Cost/Capital Expenditure	2,722	0.894	0.781	0.356
Firm	485			
Firm-Year	2,722			
Project	3,851			
Products	403			

Table 1: Summary statistics for firms and projects

Panel A reports firm-level summary statistics for the final sample of firms with at least one investment project in the CapEx dataset. The wage bill includes all the different forms of compensation to employees (wages, bonuses, etc.). R&D is the research and development expenses. Training expenses are expenditures for employee training. Intangible investment is defined as the sum of R&D and 0.3 $\times$ SG&A (selling, general, and administrative) following Peters and Taylor (2017). Panel B reports summary statistics of projects completed by the sample of firms used in the paper. Duration refers to the length of the project from announcement to completion date. Sum Project Cost is the sum of all project costs in one year. Capital Expenditure is defined as the change in PPE plus depreciation. The sample period is 1995 to 2003.

UIC measures the cost required for a firm to create the capacity for producing "one unit" of output. Firms invest in creating capacity to produce output; that is, they purchase machinery and build factories to create and expand their ability to make products. Even if firms create the same capacity for the same product category, they might incur different costs. UIC measures the differences in costs incurred for creating the capacity to produce one unit of output. It is important to emphasize that the denominator is an ex-ante measure of capacity; that is, it is the additional capacity created by the firm at the time of investment (rather than being measured using the realized firm output).

UIC is the unit price of physical capital. Unit-price variables have been used to measure quality in other settings. For instance, Kugler and Verhoogen (2012) uses unit prices to measure the quality of material input. Like other goods, physical-capital can be heterogeneous in many dimensions (i.e., how energy efficient they are or their output quality). Unit price is a mapping of different dimensions of physical capital to a single variable.

Why does UIC measure the quality of physical capital? Suppose the difference in the unit price of physical capital does not come from the markups charged by the sellers of ohysical capital (an assumption we study in more detail in subsection 6.4). In that case, a higher UIC capital good has a higher marginal cost of production. Because it has a higher marginal cost, it is likely be of higher quality. Intuitively, UIC measures the "technology" embodied in physical capital. To the extent that differences in UIC reflect how efficiently capital transform inputs to outputs, UIC measures technological differences across capital.[19] The higher quality of physical capital can increase firm performance for the buyer of physical capital.

Higher-quality physical capital might improve firm outcomes in several ways. First, it might increase firm TFP. Second, it might produce higher-quality output. Third, a higher UIC capital good might be more durable, and thus, it lowers future repair and maintenance costs or depreciates at a slower rate. In subsection 3.3, we document evidence consistent with all of these hypotheses. Before that, we document two important descriptive findings of UIC.

[19]While more expensive physical capital are perhaps more technologically advanced than cheaper ones, it doesn't necessarily mean that they are more advanced in every dimension. However, as we document in this paper, more expensive physical capital, on average, are correlated with higher revenue components and lower costs.

3.2 Two Stylized Facts about UIC

This section documents two facts about UIC: (1) UIC displays significant variation across firms investing in the same year and (2) UIC shows a high level of persistence within the same firm over time (conditional on fixing investment projects' product category).

3.2.1 Across-Firm Variation in UIC

In this subsection, we document the extent of variation in UIC within narrowly defined product categories. Firms can choose between physical capital with differing UICs. But do they? If so, to what extent? Understanding the variation is important since it is widely documented that across firms, productivity varies significantly. If variation in UIC across firms is small, then differences in UIC are unlikely to account for large differences in TFP.[20] On the other hand, if the variation is large, UIC can be a potential explanation for differences in TFP.

To study the extent of variation in UIC, define:

$$r_x^y(l,t) = \frac{y\text{th percentile of \{UIC of investment for product l at time t\}}}{x\text{th percentile of \{UIC of investment for product l at time t\}}}$$

Consider the set of investment projects for product l at time t; then, $r_x^y(l,t)$ is the ratio of the yth percentile to the xth of UIC for these projects. Intuitively, $r_x^y(l,t)$ measures the extent of variation in UIC for product l at time t.

UIC varies significantly across firms in the same year (conditional on fixing investment projects' product category). In particular, $r_{25}^{75}(l,t)$ has a mean of 5.24. In other words, the dollar value of an investment for one firm might be 5.24 times higher than another firm in the same year and product category. However, both will have the same added production capacity. In Appendix C, we report further summary statistics documenting this pattern for $r_x^y(l,t)$.

The significant variation in UIC across firms is important for three reasons. First, as discussed earlier, it suggests that UIC can be a potential explanation for differences in TFP across firms. Second, it is in contrast to what capital vintage models predict. Even though most economic models abstract away from physical capital quality differences, capital vintage

[20]The exception is when elasticity is very large.

models are an exception. In capital vintage models, new capital is more productive than old capital. Thus, when a firm invests, it always gets the latest capital vintage. Firms own an old vintage only because of past investments. Even though capital vintage models predict the existence of different vintages of capital, but it does for firms investing at the same time, i.e., every firm invests in the latest vintage. Thus, most capital vintage models would predict the same UIC (if we interpret higher UIC as a newer capital vintage) across different firms investing in the same year. However, this is in contrast to the significant cross-sectional variation in UIC that we document. Finally, this observation raises the question that why do we observe significant differences in UIC (i.e., why doesn't every firm get the latest capital vintage, as capital vintage models would predict)? In section 5, we provide evidence that financial constraints are a potential explanation.

3.2.2 Firm-Level UIC Persistence Over Time

In this subsection, we study how persistent UIC is for a firm over time. If UIC can explain differences in TFP, we might expect firm-level UIC to be persistent because firm-level TFP is known to be persistent. To study whether UIC is persistent, we compare the difference between the UIC of a firm investing in one product category multiple times over the sample with UIC differences across different firms investing in the same product category. If firm-level UIC is persistent, we expect the former to be much smaller than the latter.

We construct variable distance$_{within,l}$ to measure the difference between the UIC of a firm investing in one product category multiple times over the sample. Similarly, variable distance$_{between,l}$ is used to measure the differences in UIC across different firms investing in the same product category. More specifically, first, we limit the sample to product categories with at least five projects in the entire sample.[21] For each product category l, we take the following steps separately. For a firm investing multiple times in a product category in one year, we take the average of $ln(UIC_{lft})$, and denote it by $\overline{ln(UIC_{lft})}$. Next, we de-trend $\overline{ln(UIC_{lft})}$ as follows: regress $\overline{ln(UIC_{lft})}$ for all firm-year pairs in category l on year with firm-fixed effects. For firm f, at time t, we de-trend the $\overline{ln(UIC_{lft})}$ by subtracting the year coefficient times year. We refer to this residual as $UICres_{lf}$. Using these de-trended

[21] We choose this limit to have enough observations to estimate a time-trend for UIC in a product category.

residuals, we define:

$$\text{distance}_{within,l} = mean_{f=f'}|UICres_{lf} - UICres_{lf'}|$$

and

$$\text{distance}_{between,l} = mean_{f\neq f'}|UICres_{lf} - UICres_{lf'}|$$

where $\text{distance}_{within,l}$ is the difference between the UIC of a firm investing in one product category multiple times in product category l. $\text{distance}_{between,l}$ is the difference in UIC across different firms investing in product category l.

We find that firm-level UIC is persistent. On average, $\text{distance}_{within,l} - \text{distance}_{between,l}$ is -1.51. Considering that $UICres_{lf}$ is in logarithms, the finding implies within-firm UIC distance is 4.5 times smaller than between-firm UIC distance, which is quite substantial. That firm-level UIC is persistence is also consistent with the observation that TFP differences across firms are persistent. This finding provides further suggestive evidence that UIC can affect TFP. In Appendix C, we provide detailed summary statistics for $\text{distance}_{within,l}$, $\text{distance}_{between,l}$, and $\text{distance}_{within,l} - \text{distance}_{between,l}$.

3.3 Correlation of UIC and Firm Outcomes

Higher UIC capital is more expensive; thus, it is likely to embody superior technology that can potentially contribute to the firm in several ways. In this subsection, we first study whether UIC is associated with TFP. In the next step, we study the correlation of UIC with different components of TFP to determine what explains the correlation of UIC and firm TFP. More specifically, TFPR is equal to revenue minus a weighted average cost of physical capital, labor, and material input. Because we have the unit price and sales data for output at product level, we can further decompose revenue into output price and a measure of output quality. We test for the correlation of UIC with proxies for these variables. Furthermore, to investigate the relationship between higher UIC and physical capital durability, we test whether higher UIC is associated with lower repair and maintenance costs.

This section serves two purposes. First, the correlations can provide suggestive evidence on whether and why physical-capital quality affects TFP. Second, a unit-price variable has been used in other research articles to measure input quality (i.e., Kugler and Verhoogen

(2012)). However, the sign of the correlations coefficients we observe in the data provides further evidence consistent with UIC being a measure of physical-capital quality.

3.3.1 UIC and Productivity

In this subsection, we test whether UIC correlates with two productivity measures: TFPR and TFPQ.[22] We follow the method proposed by Ackerberg, Caves, and Frazer (2015)[23] (ACF) to calculate TFPR and use raw material as the intermediate input.[24] TFPR captures technical efficiency, output quality, and markups. Using product-level output price, we can further study the correlation of UIC with a measure of technical efficiency: TFPQ. We calculate $\ln(\text{TFPQ}) = \ln(\text{TFPR}) - \ln(P_f)$, where P_f is the sales-share weighted average price of a firm's products.

We use the following regression specification to study whether higher UIC physical capital is positively correlated with TFP:

$$y_{ft} = \alpha_l + \alpha_s + \alpha_t + \beta \times \ln(\text{UIC}_{lft}) + \lambda X_{ft} + \varepsilon_{lft} \tag{2}$$

where f, l, s and t index for firm, product category, state of project, and year, respectively; y_{ft} is firm performance for firm f at time t; α_l, α_s, and α_t are product category, project location state, and year fixed effects, respectively; ε_{lft} is the error term; and β is the coefficient of interest. X_{ft} includes time-varying firm-level controls consisting of log(PPE) to control for differences in firms' PPE, log(total assets) to control for firm size, wage bill/PPE to control for differences in the capital-to-labor ratio, and wage bill/sales to proxy for the relative ratio of skilled labor.[25]

Controlling for the value of physical capital (log(PPE)) is important for another reason. Even if firms use physical capital with different qualities, the value of physical capital might be a sufficient statistic for capital's role in the production function. If true, we might not need information on UIC to understand the role of capital on firm productivity. However,

[22] See Foster, Haltiwanger, and Syverson (2008) and Syverson (2011) for a discussion of the relationship between different measures of productivity.

[23] All the results reported in this article are similar if we use Levinsohn and Petrin (2003) methodology for production function estimation.

[24] More details on production function estimation are provided in Appendix D.

[25] The last two control variables are used in the prior literature, as well. For instance, see Eisfeldt and Rampini (2007). Furthermore, we obtain similar results if we remove these controls.

if the value of physical capital is not sufficient, we expect to find a correlation between TFP and UIC. In other words, we are testing for whether TFP is correlated with UIC after controlling for the value of physical capital.

The regression specification in 2 has two advantages relative to regressions typically used in the literature for studying the effect of investment on firm outcomes. First, the estimate of β comes from comparing two firms that have decided to invest. Thus, they are more similar relative to a case in which we compare a firm that decided not to invest with a firm that decided to invest. Second, we compare firms that have decided to invest in the same narrowly defined product category. Controlling for narrowly defined product categories is another advantage relative to the existing literature that controls for coarser industry fixed effects.

The first two columns of Table 2 show UIC is positively correlated with TFPR and TFPQ, respectively. The column one estimate suggests that a 10% increase in UIC is associated with a 1.2% increase in TFPR. Alternatively, moving from the 25th percentile to the 75th percentile of UIC is associated with an 18.6% higher TFPR.[26] The magnitude is large relative to some other factors that have been shown to affect TFP. For instance, the seminal work of Bloom and Van Reenen (2007) document that an increase from the 25th to the 75th percentile in management score is associated with a 5.8% increase in TFPR. Thus, the correlation documented here is three times as large.[27] The column two estimate suggests that a 10% increase in UIC is associated with a 0.5% higher TFPQ. Alternatively, moving from 25th to 75th percentile of UIC is associated with an 8.1% higher TFPQ.

3.3.1.1 TFP Decomposition

TFPR is equal to the residual of revenue for a given set of input costs (physical capital, labor, and material input); therefore, it can be written as

$$\ln(\text{TFPR}) = \underbrace{\ln(\text{Revenue})}_{\text{Revenue}} - \underbrace{\{\alpha_K ln(K) + \alpha_L ln(L) + \alpha_M ln(M)\}}_{\text{Cost}}$$

where K, L, and M represent the cost of physical capital, labor and material input, respectively. Coefficients α_K, α_L, and α_M are derived at the industry level from the ACF

[26] The mean of $log(r_{25}^{75}(.,.))$ is 1.57, as documented in Table C.1.

[27] The correlations do not have a causal interpretation, so the magnitude comparison should be taken with a grain of salt.

method.[28] Furthermore, in the following subsection, we will show that under a constant elasticity substitution demand system, sales share (revenue divided by revenue of all firms in that product category) at the product level can be decomposed into output price and a measure of output quality.

Thus, the positive correlation of TFPR with UIC can come from the positive correlation of UIC with sales share, output quality, and output price or a negative correlation with labor and material input. In the following two subsections, we study the correlation of UIC and these variables.

3.3.2 UIC and Revenue: Sales Share, Price, and Output Quality

In this subsection, we study whether UIC is correlated with sales share, unit price, and a measure of output quality. Since TFPR is positively correlated with UIC, we might expect a positive correlation of UIC with sales share, output price, and output quality. Prowess product-level data allow us to compute a measure of output quality at the firm-product level. We rely on the methodology developed by Khandelwal (2010) in which quality is a residual of sales conditional on prices, assuming firms face a Constant Elasticity of Substitution (CES) demand. Therefore, one can assume that product sales share could be decomposed to output quality and output price (in the same product category). The measure of firm-product-level output quality and sales-share decomposition is provided in detail in this subsection.

We focus on the subsample of investment projects (from CapEx) for which the product category of the project can be matched to a firm's output (from Prowess) using the shared product code between the CapEx and Prowess dataset. The benefit of this approach is that Prowess has data on unit prices and quantities sold. However, not all investment projects in CapEx can be matched with a firm's output in Prowess for three reasons. First, some investment projects produce intermediate inputs used by the firm, and the output is not sold to outside customers. Product-level data for these intermediate inputs are not recorded in Prowess. Second, not all firms sell the output of an investment project in the year the project is completed.[29] Third, although the 1956 Company Act requires Indian firms to disclose product-level information in their annual report, not all firms do.[30] Our

[28] Refer to Appendix D for detailed information.

[29] For example, in the subsample of new products, the product that appears for the first time in the firm's production line, we observe that around 18% of the sample start producing in the next financial year.

[30] According to Goldberg et al. (2010b), product-level information is available for 85% of the manufacturing

final matched sample consists of 51% of the total number of investment projects. Before documenting the results, we briefly explain how we measure output quality.

Measurement of Output Quality: We proxy for output quality with the residual of sales conditional on prices assuming firms face a CES demand.[31] The residual has an intuitive interpretation. The higher the residual, the higher the sales conditional on prices, and thus the higher the quality. Intuitively speaking, when comparing two products with the same price, the product that has a higher sales should be of higher quality. This intuition is used to identify quality from unit price and sales data available in the Prowess dataset.

Although the proxies used for output quality across research articles are different, given the unit price and quantity data available, this measure is perhaps the one most widely used for output quality. Measures with similar intuition have been used in the trade and macroeconomics literature, for instance, Hummels and Klenow (2005), Khandelwal (2010), Hallak and Schott (2011), and Hottman, Redding, and Weinstein (2016).

Next, we explain the details of measuring output quality using sales-share and unit-price data. Assume that firms producing products in product category g face a CES demand, with an elasticity of substitution of σ. Thus, the representative consumer's utility-maximization problem is:

$$\max_{C_f} \left(\sum_{f\in\Omega_g}(Q_f C_f)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad \Pi_{f\in\Omega_g} Q_f = 1$$
$$\sum_{f\in\Omega_g} P_f C_f \leq K$$

where the representative consumer maximizes utility by optimally choosing the quantity of consumption of products offered by firm f, C_f, subject to the budget constraint $\Sigma_{f\in\Omega_g} P_f C_f \leq K$. Ω_g is the set of all firms offering products in product category g. P_f is the unit price of the product offered by f, Q_f is the quality of the product offered by firm f, and σ is the elasticity of substitution and measures the degree of substitution between products offered by different firms. A 1% decrease in the unit price of firm f increases its sale by $\sigma - 1$. Thus, the higher the σ, the more sensitive the representative consumer is to unit prices.

firms that account for about 90% of output.

[31] This measure of output quality can have two interpretations here. First, it can capture differences in consumer tastes. For instance, more people might prefer black hard drives rather than blue hard drives. Thus, black hard drives will have higher quality. Second, it can capture differences in ranking common across all consumers. Thus, a faster hard drive has higher quality than to a slower one.

Solving the optimization problem to find the optimal C_f, and rearranging:

$$\ln(Q_f) = \frac{\sigma}{\sigma-1}\ln(P_f) + \frac{1}{\sigma-1}\ln\left(\frac{P_f C_f^*}{\Sigma_g P_f C_f^*}\right) + \frac{1}{\sigma-1}\ln\left(\Sigma_f P_f^{-\sigma} Q_f^{\sigma-1}\right) \tag{3}$$

where C_f^* is the optimal consumption of firm f's product in product category g. The equation has an intuitive interpretation: if two products have the same unit prices (P_f), the product with higher quality (Q_f) has a higher sales share $\left(\ln\left(\frac{P_f C_f^*}{\Sigma_g P_f C_f^*}\right)\right)$. Furthermore, the more substitutable the products are (higher σ), the higher the sales share of a product with higher quality.[32] Alternatively, output quality ($\ln(Q_f)$) is the residual of sales share of product f (more precisely, the term $\frac{1}{\sigma-1}\ln\left(\frac{P_f C_f^*}{\Sigma_g P_f C_f^*}\right)$), conditional on unit price (more precisely, the term $\frac{\sigma}{\sigma-1}\ln(P_f)$).

The set of equations in 3 is used to back out output quality from unit price and sales data. If we assume a value for σ, the only unknown for each firm is product quality, Q_f. Because we have one equation for each unknown, a unique solution exists that satisfies Equation 3 for every firm.[33]

Columns 3-5 of Table 2 show the results of regression 2 for price, quality, and sales share, respectively. Column (3) shows a that a 10% increase in UIC is associated with a 1% increase in unit output price. Alternatively, moving from the 25th to the 75th percentile is associated with a 15.5% increase in unit output price. A positive correlation of UIC with unit price echoes the findings in Kugler and Verhoogen (2012) and the literature thereafter that documents a positive correlation of output and material input price. Column 4 shows the results of regression specification 2, where output quality is measured using $\ln(Q_f)$ defined in equation 3. We assume that the elasticity of substitution, $\sigma = 5$, for all product categories.[34]

[32]The term $\frac{1}{\sigma-1}\ln\left(\Sigma_{f\in\Omega_g} P_f^{-\sigma} Q_f^{\sigma-1}\right)$ is constant for all products offered in the same product category. The constant is such that $\sum_{f\in\Omega_g}\ln(Q_f) = 0$, because we have assumed $\Pi_{f\in\Omega_g} Q_f = 1$.

[33]To be precise, because we have assumed $\Pi_{f\in\Omega_g} Q_f = 1$, the number of unknowns is equal to the number of equations minus one. However, the equations are not independent either. In particular, since $\sum_{f\in\Omega_g}\ln(Q_f) = 0$, the number of independent equations is the number of equations minus one, as well. Thus, the number of unknowns is equal to the number of independent equations, and thus a unique solution exists.

[34]Our choice of σ is motivated by the macroeconomics and international trade literature, where the CES demand system is widely used. Our product-level data are granular, and the estimated elasticities in trade literature for this level of granularity tend to be high. See, for example, Broda and Weinstein (2006). Furthermore, the magnitude of the estimated coefficient is not sensitive to the choice of σ. We obtain similar

The estimate suggests that a 10% increase in UIC is associated with a 1.3% increase in output quality. Alternatively, moving from the 25th to the 75th percentile of UIC is associated with a 20.5% increase in output quality. Column 5 estimate suggests that a 10% increase in UIC is associated with a 0.4% rise in sales share. Alternatively, moving from the 25th to the 75th percentile of UIC is associated with a 6.6% increase in sales share.

The correlations in columns 3-5 have a unique feature: a direct link exists between physical capital and output for multi-product firms. This point is important because most other studies establish an indirect link between input and output for multi-product firms (see i.e., Kugler and Verhoogen (2012)). They use either a third variable (for instance, size) or need to make assumptions about how different inputs are aggregated (i.e,, CES aggregator). To the best of our knowledge, this direct link between an input and output in multi-product firms is unique to this dataset.[35]

In Appendix E, we show that the correlation between UIC and a dummy for export, as another measure of output quality, is positive. The international trade literature has widely documented that companies that export goods in developing countries, on average, produce higher-quality goods. Thus, we use a dummy variable for exporting to proxy for the production of high-quality output. The results in Appendix E provide further support for the hypothesis that high UIC capital enables firms to produce high-quality output.

To sum up, thus far, we have shown high UIC capital is positively correlated with TFP, sales share, output price, and output quality. However, high UIC capital might benefit firms through another channel by reducing other costs associated with the production of goods, specifically by reducing labor and material input costs. We study this possibility in the next subsection.

3.3.3 UIC and Cost

In this subsection, we study the correlation of UIC with labor and material input. Because TFP is positively correlated with UIC, we might expect a negative correlation between UIC

coefficients for $\sigma \in \{3, 5, 10\}$.

[35] A measurement difference between our paper and that of Kugler and Verhoogen (2012) also exists. Whereas they use unit prices of input, how the unit price of input maps to the unit of output in the absence of detailed information about production function in multi-product firms is not clear. However, we use unit cost per unit of output, because our dataset has data on the capacity of the production added to the firm. Thus, our measurement is perhaps finer.

and the cost of labor and material input. To proxy for the cost of labor and material input, we use total wages and raw-material input divided by sales.[36,37]

Columns 6-7 of Table 2 show the estimated coefficients of regression specification 2 for total wages/sales and material input/sales, respectively. Column 6 estimates suggest that a 10% increase in UIC is associated with a -0.6% lower total wages/sales. Alternatively, moving from the 25th to the 75th percentile of UIC is associated with a 10% decrease in wage bill/sales. This finding is consistent with the idea that higher UIC capital can potentially substitute for labor costs. If UIC is interpreted as the "technology embodied" in capital, the findings here are consistent with the idea that "technology" substitutes for labor. Column 7 of Table 2 suggests that a 10% increase in UIC is associated with a -0.4% cost of material input normalized by total sales. More specifically, moving from the 25th percentile to the 75th percentile is associated with a 6.4% decrease in the cost of material input/sale.

So far, we have documented the positive correlation between UIC and TFP and output quality. All the results documented so far are for the year that the project was completed. However, physical capital is durable, and sometimes it lasts for decades. Thus, higher UIC might last longer.

3.3.4 UIC and Durability

Is higher UIC physical capital more durable? Measuring the durability of capital is difficult because we don't observe direct durability measures in our data. We use repair and maintenance cost as a proxy for durability. We assume a physical capital that is less costly to maintain is more durable. What is the logic behind such an assumption? We assume the closer we get to the end of the life of the capital, the costlier it gets to maintain (they break more often). Thus, repair and maintenance cost proxies for the durability of capital.

Column 8 of Table 2 shows UIC is negatively correlated with repair and maintenance cost/PPE. The estimate suggests that a 10% increase in UIC is associated with a -0.2% decrease in repair and maintenance cost/PPE. In particular, moving from the 25th to the

[36]We use total wages rather than the wage per employee because the Prowess dataset does not include information about the number of employees. We find similar results when we normalize total wages and material input by assets, as well.

[37]We can also use the weighted average material input price for the firm as a proxy for material input. Hallak and Sivadasan (2013) used such a proxy, where the weight of each input price is the share of the input in total input costs. Although it causes a loss of 25% of data, we find similar results.

75th percentile is associated with a 3% lower repair and maintenance cost/PPE. The negative correlation suggests that higher UIC physical capital is more durable.

	Productivity		Revenue			Cost		Durability
	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Sales Share)	ln(Wage Bill)	ln(Material Expense)	ln(Maintenance)
ln(UIC)	0.119**	0.051**	0.099***	0.134***	0.042**	-0.064***	-0.041**	-0.019**
	(0.048)	(0.023)	(0.021)	(0.031)	(0.017)	(0.022)	(0.016)	(0.007)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.625	0.591	0.901	0.876	0.854	0.371	0.386	0.351
Observations	3851	3701	1953	1953	1953	3851	3851	3394

Table 2: UIC and firm outcome correlation

This table reports the estimates of regressions 2 for productivity, revenue, cost, and durability. UIC is defined using equation 1 for each investment project. We include one observation per project for the year the project was completed. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output quality derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. The wage bill includes all the different forms of compensation to employees (wages, bonuses, etc.) divided by sales. Material expense is the total payment for material inputs divided by sales. Maintenance is the repair and maintenance cost divided by PPE. Controls include: log(PPE), log(total assets), wage bill/PPE (except for the wage-bill regression), and wage bill/sales (except for the wage-bill regression). All regressions include fixed effects for the product, project location's state, and year. Standard errors are double-clustered at year and firm-level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

3.3.5 UIC and Scope for Quality Differentiation

This subsection studies whether UIC is more correlated with TFPR, TFPQ, sales share, output price, and output quality in industries with higher scopes for quality differentiation. We use two measures of scope for quality differentiation following the literature. These measures capture the heterogeneity in the benefits of producing higher-quality output across different industries. Using these measures, we can provide further evidence that high UIC physical capital increases firm performance by enabling firms to produce higher-quality output.

We focus on output quality because increased output quality is particularly important for economic growth in developing countries.[38] Furthermore, using output quality, we can

[38]Refer to quality-ladder literature originated in Grossman and Helpman (1991). Furthermore, Atkin et al.

provide a unified explanation for why higher UIC capital are correlated positively with TFPR, sales share, price, and quality. The role of high UIC physical capital in producing high-quality output is similar to the mechanism suggested in Kugler and Verhoogen (2012), who find that using higher-quality input is more strongly associated with higher-quality output. Next, we explain how we measure the scope for quality differentiation.

Measurement of Scope for Quality Differentiation: The first measure of scope for quality differentiation is R&D and advertising expenditures divided by total sales at the four-digit NIC industry following Kugler and Verhoogen (2012). Prowess data does not provide adequate information on R&D or advertising expenditures. Instead, we use industry-level information on R&D and advertising expenses from the U.S. Federal Trade Commission (FTC) Line of Business Survey, a source that other researchers have used to measure the scope for quality differentiation, including Kugler and Verhoogen (2012) and Sutton (2007). Appendix F contains the details of constructing the measure. We use $scope_{R\&D}$ to refer to this measure.

The second measure of scope for quality differentiation is the sales-weighted average of the standard deviation of the logged value of quality ($\ln(Q_f)$, the variable defined in section 3.3.1) in four-digit NIC industry codes. Fan, Li, and Yeaple (2018) use a similar method to measure the scope of quality differentiation.[39] More specifically, for a given product l at time t, we calculate the standard deviation of $\ln(Q_{lft})$ for the subsample of firms offering product l in year t. Then, we take the average overtime to get a measure of quality dispersion for product category l, $scope_{quality}(l)$. Finally, we use the sales-weighted average of $scope_{quality}(l)$ to get a four-digit NIC measure of scope for quality differentiation. Thus, the second measure of scope for quality differentiation for industry k is:

$$scope_{quality}(k) = \sum_{l \in \Omega_k} \omega_l scope_{quality}(l) \tag{4}$$

where ω_l is the average sales share of product l in industry k, and Ω_k is the set of firms in industry k.

Appendix F contains more details about the construction and summary statistics for the

(2017) and Bastos et al. (2018) note that as global incomes rise, access to wealthier and quality-sensitive markets increases output quality returns.

[39] Fan et al. (2018) use quality variances in a product category to divide the sample to construct a homogeneity dummy where the dummy takes the value of one for goods with below-median quality variance.

two measures. Overall, 91 four-digit NIC industry codes exist. The average and standard deviation of $\ln(scope_{R\&D})$ are -4.42 and 1.31, respectively. The average and standard deviation of $\ln(scope_{quality})$ are 0.54 and 0.75, repectively. The correlation between the two measures is 0.74. Reassuringly, that the correlation between these two measures is high because they capture the same concept.

To study interaction with scope for quality differentiation, we use the following regression specification:

$$y_{ft} = \alpha_l + \alpha_s + \alpha_t + \beta_1 \times \ln(\text{UIC}_{lft}) + \beta_2 \times \ln(\text{UIC}_{lft}) \times scope_{R\&D} + \lambda X_{ft} + \varepsilon_{lft} \tag{5}$$

All the control variables and the fixed effects are the same as equation 2. The only difference is that the above regression has the interaction term, $\ln(\text{UIC}_{lft}) \times scope_{R\&D}$.

Columns 1-2 of Table 3 reports the result of regression 5 for TFPR and TFPQ. We show the results using $scope_{R\&D}$ interactions in the paper and using $scope_{quality}$ in Table 3 of Appendix J. Using both measures, we find similar results. For ease of interpretation, we have deviated $\ln(scope_{R\&D})$ by its median. In column 1, we estimate that a 10% increase in UIC is associated with $10 \times (0.106 + 1.311 \times 0.087) = 2.16\%$ increase in TFPR of firms that belong to an industry with one standard deviation higher $ln(scope_{R\&D})$ than the median.[40] Similarly, our estimates show a 10% increase in UIC is associated with a 0.96% higher TFPQ in an industry with one-standard-deviation-higher $\ln(scope_{R\&D})$ than the median. The magnitudes of the interaction terms are large and suggest that producing higher quality goods is an important driver of choosing UIC. Despite the significant interactions, the UIC and TFP correlations are not limited to a few industries because all the coefficient estimates for the uninteracted terms are positive and significant, as well.

Columns 3-5 of Table 3 shows the result of regression 5 with the interaction term $\ln(\text{UIC}) \times \ln(scope_{R\&D})$ for price, quality, and sales share. In column 3 we estimate that a 10% increase in UIC is associated with a $10 \times (0.095 + 1.311 \times 0.073) = 1.97\%$ increase in unit output price for firms that belong to an industry with one-standard-deviation-higher $\ln(scope_{R\&D})$ than the median. Similarly, our estimates show a 10% increase in UIC is associated with a 2.6% and 0.8% higher output quality and sales share in an industry with one-standard-deviation-higher $\ln(scope_{R\&D})$ than the median, respectively.

[40] The standard deviation of $\ln(scope_{R\&D})$ is 1.31.

	Productivity		Revenue		
	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Sales Share)
ln(UIC)	0.106**	0.048**	0.095***	0.128***	0.040**
	(0.043)	(0.021)	(0.021)	(0.031)	(0.017)
ln(UIC) $\times$ ln(scope$_{R\&D}$)	0.087**	0.037*	0.073***	0.098**	0.029**
	(0.039)	(0.020)	(0.021)	(0.038)	(0.012)
Controls	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
R^2	0.631	0.597	0.968	0.963	0.918
Observations	3851	3701	1953	1953	1953

Table 3: Heterogeneity in UIC and firm outcome correlations: Interaction with scope for quality differentiation

This table reports the estimates of regressions 5. UIC is defined using equation 1 for each investment project. We include one observation per project for the year the project was completed. scope$_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln(scope$_{R\&D}$) has been deviated from the sample median. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output quality is derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the product, the project location's state, and year. Standard errors are double-clustered at year and firm-level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

3.4 Discussion: Interpretation and Magnitude of the Estimated Coefficients

Firm-Level Regressions in Multi-Product Firms: In regression specification 2, the left-hand-side variable is at the firm level, but ln(UIC) is at product level. Thus, the estimated coefficient might be biased. First, the direction of bias is likely toward zero, because, in Appendix C.3, we document that the correlation of UIC rank (across all firms investing in the same product category) for different products of the same firm is positive but small. In other words, if a firm is investing in a high-UIC project in one product category, it is only slightly more likely to invest in a high-UIC project in another product category. Thus, looking at the firm-level outcomes is likely to bias the coefficients toward zero. Second, we repeat our analysis for the subset of single-product firms in Appendix G.1. This subsample is fairly large and consists of nearly half of the product-year observations. We find similar results in this subsample as well.

UIC of Investment vs. the UIC of Capital Stock: We cannot identify which product is produced by the new investment projects (data from CapEx) and which products are produced using the existing capital stock. Thus, the coefficients might be biased. We take the following steps to address this issue. First, in Appendix G.2, we repeat the same exercise for the subsample of projects with new products. For new products, we know the firm can produce the product because of the new investment.[41] This subsample is fairly large and consists of nearly 35% of the product-year observations. We find similar results using this subsample as well. Second, as documented in 3.2.2, the product UIC is persistent over time. Thus, the firm's product using the existing capital stock is more likely similar to its products using newly invested physical-capital (relative to other firms' products). Studying the stock market's response to UIC news at the time of the project announcement would be another way to address this issue, which will be covered in detail in the Appendix L.

Can the correlations in Tables 2 and 3 be rationalized in a model? In the next section, we develop a stylized model that can explain the main findings of both tables.

4 A Stylized Model of Firms with UIC and Financial Constraints

This section develops a stylized model of endogenous choice for UIC in the presence of financial constraints. Despite its simplicity, the model can generate the main correlations that we observe in the data. We focus on financial constraints as one of the main sources of heterogeneity across firms for two reasons. First, financial constraints are well documented as an important factor in a firm's investment decisions. Second, we study a quasi-natural experiment in the next section that reduces the costs associated with debt-contract enforcement. Thus, a model of financial constraints helps interpret those results, as well.

The model can be briefly summarized as follows. Two sources of heterogeneity across

[41] A new product is a product that appears for the first time in the set of products sold by the firm.

firms exist. First, within an industry, firms only differ in how financially constrained they are. Second, across industries, differences in scope for quality differentiation exist. The higher the scope for quality differentiation, the greater the payoff from producing higher-quality output. Higher UIC investment increases output quality and reduces the future cost of production. Firms face constant elasticity of substitution (CES) demand and can invest only by borrowing. To produce, they need to invest, and they choose both UIC and the dollar value of the investment. The model can generate the main correlations that we observe in the data.

The model developed here is perhaps closest to Kugler and Verhoogen (2012). Their input quality parameter can be interpreted as UIC in our setting. The main difference comes from why different firms choose different input qualities. In our model, financial constraints are the reason. In theirs, differences in initial productivity draw. explain the choices. Below, we explain the details of the model.

4.1 Model Set-up

The economy consists of a monopolistically competitive final-goods sector and a perfectly competitive, constant-returns-to-scale physical-capital sector. We begin by analyzing the final-goods sector. A representative consumer has the following standard asymmetric constant elasticity-of-substitution utility function over final goods:

$$U = \left(\Sigma_{\omega \in \Omega} (q(\omega) x(\omega))^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where ω indexes varieties in the final-goods sector, Ω is the set of all differentiated varieties, σ is the elasticity of substitution between varieties,[42] $x(\omega)$ is the quantity of variety ω consumed, and $q(\omega)$ is the quality of variety ω. Here, output quality, $q(\omega)$, can be interpreted as any product attribute that the representative consumer values. It is a choice variable for firms and is a function of the UIC of the physical capital used for production. The specific functional form is discussed later.

Solving the consumer optimization problem, variety ω has the following demand function:

$$x(\omega) = X q(\omega)^{\sigma-1} \left(\frac{p_{out}(\omega)}{P} \right)^{-\sigma} \tag{6}$$

[42]We make the standard assumption that $\sigma > 1$.

where $p_{out}(\omega)$ is the price of the variety ω, P is the aggregate quality-adjusted price index, and X is the quality-adjusted consumption aggregate of the available varieties.[43] Demand is increasing in output quality and decreasing in the price. For convenience, we drop ω. Each firm is small relative to the market size, and thus it ignores the effects of its decisions on the aggregates X and P.

We assume producers of physical capital are competitive.[44] Each unit of physical-capital with a quality of u is sold for a price u. In this model, u represents UIC. The key point is that a linear relationship exists between the quality of physical capital and its price from the perspective of final-goods producers. So far, our model is the same as Kugler and Verhoogen (2012).

Output Quality and UIC: We assume output quality is a function of u, physical-capital quality. Characterizing the equilibrium of the model with a general production function for quality becomes intractable. Instead, we consider a special case in which output quality, q, is a power function of the physical-capital quality, u:

$$q = u^{\beta} \tag{7}$$

The positive parameter β in equation 7 is the scope for quality differentiation. The parameter captures differences across different industries in benefits from quality differentiation. In other words, using high-quality physical capital in industries with high β is more beneficial because the output quality will be higher. Although not explicitly specified in the model, one could also think of β as capturing the willingness of consumers to pay for product quality. The key point is that a higher β gives firms more incentives to use higher-quality physical capital for production.

[43]Specifically, $X = \left(\Sigma_{\omega\in\Omega}(q(\omega)x(\omega))^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ and $P = \left(\Sigma_{\omega\in\Omega}(\frac{p_{out}(\omega)}{q(\omega)})^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$.

[44]Because we are not interested in the general equilibrium effects of the proposed model, we do not need to introduce a physical-capital sector in detail. However, in this footnote, we follow the tradition of Melitz (2003) and briefly describe the assumptions needed to have a competitive physical-capital sector. We assume an inelastic labor supply L (measured in labor hours) with the hourly wage normalized to one. In the model, the physical capital sector transforms homogeneous labor-hours into physical-capital of different qualities. In the physical-capital sector, the production function is $F(l,u) = \frac{l}{u}$, where u is the quality of the physical-capital produced and l is the number of labor-hours used. In other words, producing one unit of capital good with quality u requires u labor hours. With each unit of labor-hour costing one, capital with quality u costs u. If final-good producers are price-takers and the market is perfectly competitive, in equilibrium, the price of the capital good of quality u equals the marginal cost of production u.

Production Cost: We assume increases in physical-capital quality reduce costs as well. This assumption is motivated by the evidence in Table 2, in which we see a negative correlation between UIC and wage bill and material input. Our model assumes the production function does not have labor and material input for simplicity. However, the relationship between UIC and labor and material input shows up implicitly through the cost function. We model the cost reduction per unit of output by the function $c(u)$. $c(u)$ is a decreasing function in u. The specifics of the functional form assumptions for $c(u)$ is explained later.

Financial Constraint We assume firms need financing to purchase physical-capital. They can borrow up to a maximum of an exogenously determined amount, A. Alternatively, A can be interpreted as the degree of financial development. The more financially developed a country becomes, the more firms in the country can borrow, and thus the higher the A. This source of heterogeneity across firms within an industry (firms in an industry have the same scope for quality differentiation, β) is the only one. Investing in x_C units of capacity with UIC, u, costs $x_C u$. Thus,

$$x_C u \leq A \tag{8}$$

For simplicity, we assume firms produce with full capacity $x = x_C$.

4.2 Firm's optimization problem

The firm's maximization problem is

$$\max_{p_{out},u} \pi(p_{out}, u; A) = (p_{out} - c(u) - u)x$$

Subject to

$$xu \leq A$$

where $x = Xq^{\sigma-1}\left(\frac{p_{out}}{P}\right)^{-\sigma}$ from (6), and $q = u^{\beta}$.

4.3 Equilibrium

The following two propositions characterize the equilibrium solution. For proofs, refer to Appendix H.

Proposition 1: For each $\beta < 1$, a threshold $\bar{A}_\beta$ exists such that[45]
(i) If $A < \bar{A}_\beta$, the borrowing constraint is binding and the firm produces suboptimally.
(ii) If $A \geq \bar{A}_\beta$, then the borrowing constraint is not binding, and the firm produces at first best, and the optimal solution is independent of A.

Proposition 1 is a standard prediction of a model with financial constraints. When a firm can borrow more than a threshold, $A \geq \bar{A}_\beta$, the firm is not financially constrained and will produce at first best independent of A (of course, given that financial constraint is the only friction in the model). The more interesting case is when the firm produces suboptimally. Proposition 2 characterizes the solution for a firm that is financially constrained, namely, $A < \bar{A}_\beta$.

Proposition 2: If $c(u) = max\{a - bu^k, 0\}$ where a and b are positive numbers, in the constrained region ($A \leq \bar{A}_\beta$) if an interior solution exists,[46] then the following inequalities hold[47]:
(i) $\frac{\partial u}{\partial A} > 0$
(ii) $\frac{\partial x}{\partial A} > 0$ iff the scope for quality differentiation (β) is low
(iii) $\frac{\partial^2 u}{\partial A \partial \beta} > 0$
(iv) $\frac{\partial^2 x}{\partial A \partial \beta} < 0$
(v) $\frac{\partial p_{out}}{\partial u} > 0$ and $\frac{\partial p_{out}}{\partial A} > 0$
(vi) $\frac{\partial size}{\partial u} > 0$ and $\frac{\partial size}{\partial A} > 0$
(vii) $\frac{\partial \pi}{\partial u} > 0$ and $\frac{\partial \pi}{\partial A} > 0$
(viii) $\frac{\partial^2 p_{out}}{\partial A \partial \beta} > 0$ and $\frac{\partial^2 p_{out}}{\partial u \partial \beta} > 0$
(ix) $\frac{\partial^2 \pi}{\partial A \partial \beta} > 0$ and $\frac{\partial^2 \pi}{\partial u \partial \beta} > 0$
(x) $\frac{\partial u}{\partial \beta} > 0$ and $\frac{\partial x}{\partial \beta} < 0$

We briefly explain each of the results in Proposition 2. (i) shows UIC (u) is an increasing function of A (which measures the maximum that the firm can borrow, and thus, higher A is equivalent to more relaxed financial constraints). (ii) documents that an increase in A can

[45] The assumptions $\beta < 1$ will ensure the existence of an interior solution for the unconstrained case.

[46] The assumptions $1 < k < 1 + \beta_{min}$ will ensure the existence of an interior solution in the constrained case.

[47] We assumed a functional form for cost function $c(u)$ to make the equilibrium more tractable. The functional form has intuitive properties: it is bounded, positive, and is decreasing in u. A negative correlation between UIC and production costs in the data is documented in subsection 3.3.3.

decrease or increase the quantity of output. If the scope for quality differentiation is high enough, the firm reduces the quantity of output to increase UIC. On the other hand, if the scope for quality differentiation is low, the firm increases the quantity of output. (iii) shows an increase in A increases UIC more in industries with higher scope for quality differentiation. (iv) shows an increase in A decreases the quantity of output (x) more in industries with higher scope for quality differentiation. (v), (vi), and (vii) document that output price, firm size (measured as $p_{\text{out}}.x$), and firm profit, respectively, are positively correlated with both A and UIC. (viii) and (ix) show output-price and firm-profit correlation with both UIC and A are higher in industries with more scope for quality differentiation.

The model serves two purposes: first, it shows a theoretically consistent framework that generates empirical patterns documented in the previous section. Second, we study how the heterogenous firms' ability to borrow affects the choice of UIC using a quasi-natural experiment setting that we explain in the next section. The model produces results consistent with that setting, as well.

Figure 2 plots a numerical example for the results in Proposition 2. The top-left panel plots UIC as a function of A. UIC is an increasing function of A. The top-middle panel plots quantity as a function of A. For low scope for quality differentiation (small β), quantity is increasing in A, but for high scope for quality differentiation (large β), it is increasing initially, then decreasing until it reaches the first-best solution. The top-right panel plots the total cost (UIC plus the other costs (for instance, labor)) per output unit. It is an increasing function of UIC (A). The bottom-left and bottom-middle panels plot quality and price, respectively. Finally, the bottom-left panel plots profit as a function of A.

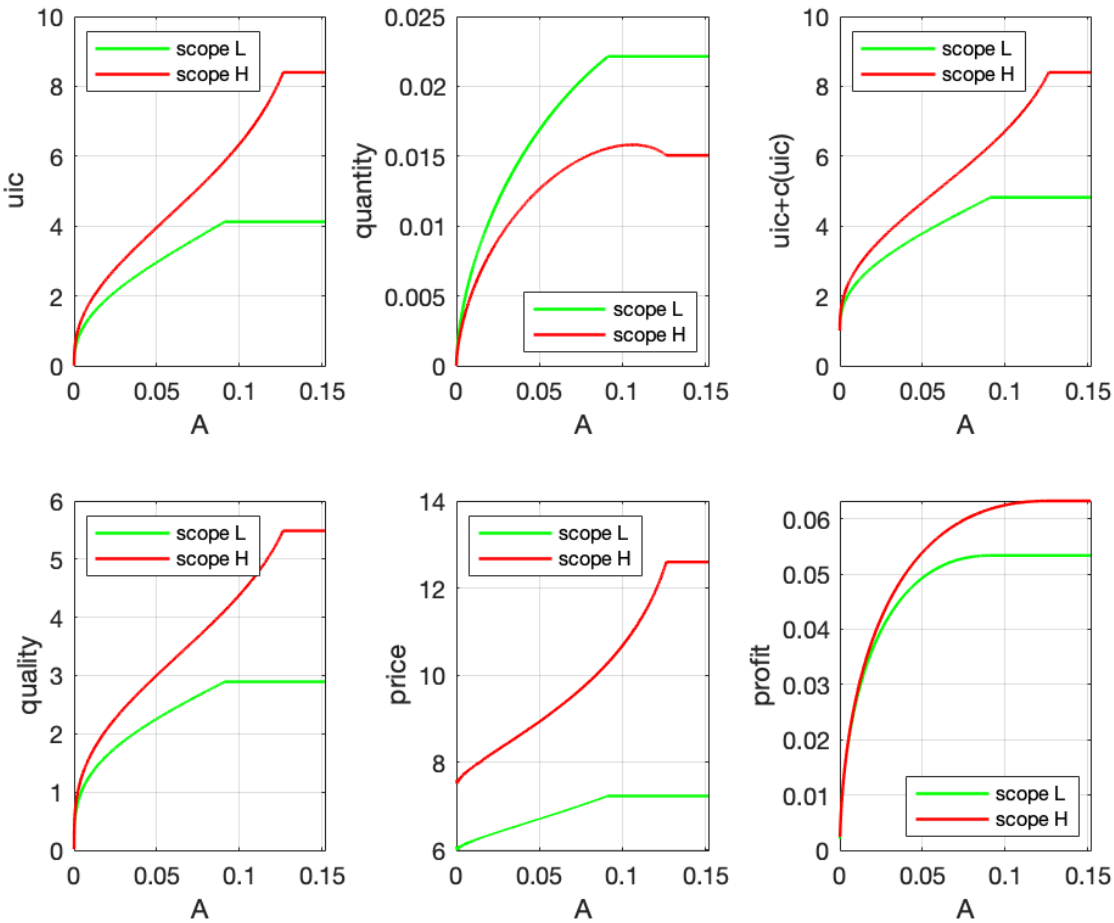

Figure 2: Outcome variable of interest with respect to maximum that firm can borrow
This graph plots the outcome variables of interest with respect to A. A is the maximum amount of debt that the firm can borrow. Quantity is the both the quantity of output and capacity. uic + c(uic) is the marginal cost of producing one unit of output. Quality is derived from equation 3. The parameters used for model simulation are $\beta_L = 0.75$ (for low scope for quality differentiation, "scope L"), $\beta_H = 0.8$ (for high scope for quality differentiation, "scope H"), $a = 1$, $b = 0.028$, $k = 1.68$, $\zeta = 1$, and $\sigma = 3$.

5 A Quasi-Natural Experiment, UIC, and Firm Performance

5.1 Background of the DRT law

In the early 1990s, banks and financial institutions in India facing high volumes of non-performing loans. The debt-recovery rates were low, partly because these default cases were being processed in the inefficient civil court systems. For example, a survey by the government of India in 1988 found that around 40% of the pending debt-recovery cases in 1985-1986 had been pending for more than eight years.

In 1993, the government of India passed the Debt Recovery Tribunal (DRT) Act to establish DRTs across different states in the country. DRTs are courts specialized in corporate-loan-default cases. After the passage of the law, banks and financial institutions could file suits for claims larger than 1 million Indian rupees in these specialized courts.

As documented in Visaria (2009), the law was effective in reducing the enforcement costs associated with debt recovery. In particular, DRTs significantly reduced the delay in processing the debt-recovery cases. For instance, Visaria (2009) documents that for a random sample of lawsuits of a large Indian bank, the DRTs reduced the average time to complete hearings by more than 2,000 days, as compared with the civil courts. The reduced delay in processing the debt-recovery cases effectively increased the value of the defaulted loan for the lender. Furthermore, the author provides evidence that DRTs reduced the likelihood of delinquency of an average loan by about 28%. Thus, DRTs were effective in debt-recovery costs.

Consequently, banks and financial institutions had more incentives to lend. In other words, higher ex-post efficiencies in debt recovery increase the ex-ante bank's incentives to lend in the first place. This is indeed what happened after the introduction of DRTs, and is documented in Gopalan et al. (2016). Thus, we use the introduction of the DRTs as an exogenous increase in banks' incentives to lend.

We use the staggered introduction of DRTs across different states from 1995 to 2000 for identification and compare firms with headquarters located in states with and without DRTs. The identification is the same as in Gopalan et al. (2016), Visaria (2009), and von Lilienfeld-Toal et al. (2012). Even though the law was passed in 1993, DRTs were not established in all states at the same time, due to the legal challenges that the government faced when establishing DRTs across different states.[48] Eventually, the country's supreme court ruled in favor of establishing DRTs across all states, and by 2001, all states adopted DRTs. Table I.1 in Appendix I.1 lists the adoption date of DRTs for each state. Two details are important in the establishment of DRTs. First, states did not have the authority to establish DRTs on themselves, and establishing these specialized courts was at the discretion of the Indian government. This fact alleviates some concerns about the endogeneity of the timing of DRT establishment across different states. Second, all eligible cases were transferred from civil courts to DRTs, and firms and banks had no discretion to decide whether a DRT or a civil court rules in a case. This fact further alleviates concerns about the endogeneity of firms' and banks' choice to be treated or not after the establishment of DRTs.

Thus, the identification assumption is that the timing of the passage of the DRTs across different states was irrelevant to the average state or firm-level characteristics. This is likely to hold for two reasons. First, the details of DRT establishment and the reasons for its staggered implementation across different states suggest this assumption is likely to hold (for more details, refer to Visaria (2009) and Gopalan et al. (2016)). Second, we conduct a pre-trend test in Table I.2 in Appendix I.1 and find no evidence of a pre-trend. These findings are consistent with those of Gopalan et al. (2016) and von Lilienfeld-Toal et al. (2012), who also do not find evidence of a pre-trend.

5.2 Effect of DRT Establishment on Debt, Investment, UIC, and Additional Capacity

Debt and Investment: We begin our empirical analysis by documenting how firms' debt and investment respond to the establishment of DRTs. We estimate the following staggered difference-in-difference regression:

$$y_{ft} = \alpha_f + \alpha_t + \alpha_s + \beta \times \mathrm{DRT}_{st} + \lambda X_{ft-1} + \varepsilon_{ft} \tag{9}$$

where f indexes firm, s indexes the firm's state of incorporation, t indexes time, and y_{ft} is the variable of interest at the firm level. α_s, α_f, and α_t, are the state of incorporation,[49] firm,

[48] For a detailed discussion about these challenges, please refer to Visaria (2009).

[49] The firm's state of incorporation will be absorbed by firm fixed effects.

and year fixed effects, respectively. X_{ft-1} are time-varying firm-level control variables and are the same as the previous specifications.[50] DRT$_{st}$ is a dummy variable equal to one if a DRT has been established by time t in state k, and ε_{ft} is the error term. β is the coefficient of interest and measures the effect of the establishment of DRTs on the outcome variable of interest. Year refers to the financial year, which is the end of the last day of March for the next calendar year.

The first two columns of Table 4 report the estimates for total debt and investment using regression specification 9. In this table, investment is measured using the balance-sheet variables. We use "balance-sheet CAPEX" to refer to Δ PPE plus depreciation. Because we have data on project cost, we can measure investment using the project cost in CapEx. We find similar results using both measures as extensively documented in Appendix I.3. In column 1, we find the establishment of DRTs leads to a statistically and economically significant increase in the debt level. We estimate that DRT establishment increased firm-level debt by 6%. This finding is consistent with the idea that DRT establishment increasED banks' incentives to lend due to the improved recovery rates in case of default. This result is in line with findings in Gopalan et al. (2016) studying the same setting.[51] In column 2, we find that introduction of DRTs increased balance-sheet CAPEX by 4%, consistent with the idea that the increased debt increased firm-level investments.

UIC and Additional Capacity: Increased investment can come from firms investing in higher-UIC capital, increasing capacity, or both. Next, we decompose the effect of DRT establishment on project cost to its effect on UIC and capacity. By definition (from equation 1) we have:

$$\ln(\text{Project Cost}_{lft}) = \ln(\text{UIC}_{lft}) + \ln(\text{Capacity}_{lft})$$

We use the following regression specification to study the effect of the DRT establishment

[50] We use the lagged control variables to make sure the inclusion of control variables does not bias the estimates.

[51] Gopalan et al. (2016) estimates the effect of DRT establishment on short-term and long-term debt separately. They use a fully saturated model, similar to what we do in the pre-trend analysis in Appendix I.2. Although the sample of firms studied in our paper is different, their estimated magnitude falls within a 95% interval of ours.

on project cost, UIC, and additional capacity:

$$y_{lft} = \alpha_l + \alpha_t + \alpha_s + \beta \times \mathrm{DRT}_{st} + \lambda X_{ft-1} + \varepsilon_{lft} \tag{10}$$

The regression is similar to 9. The only difference is that instead of using firm fixed effects (α_f), we use product-group fixed effects (α_l). β is the coefficient of interest and estimates the effect of the establishment of DRTs on the outcome variable of interest.

Columns 3-5 of Table 4 document the results of regression 10 for project cost, UIC, and additional capacity. In column 3, we estimate that firms in treated states increased investment in projects by 9.2%, which is both economically and statistically significant. In column 4, we find the establishment of DRTs leads to a 10.3% increase in UIC, which is statistically and economically significant. The last column shows the estimated coefficient for the additional capacity. The estimated coefficient is statistically insignificant and small.

Findings in Table 4 further highlight the importance of UIC in understanding investment decisions, because for an average firm, all the increase in investment comes from increased UIC. Because this article is the first to study UIC, we don't know if this finding is robust in other settings. Even though we don't know of any article that analyzes investment decomposition to UIC and additional capacity, Goolsbee (2004) is perhaps the closest empirical study because that article decomposes investment into the price and quantity of machine equipment. Goolsbee (2004) uses the Current Industrial Report (CIR) data from 1960-1988. The dataset includes the number and price of machinery for narrowly defined physical-capital categories in three industries: farming, construction, and mining. Goolsbee (2004) uses the data to study the effects of investment tax subsidies on investment, the number, and the price of machinery purchased. He finds that tax subsidies increase investment, and all the effect of investment tax subsidies comes from purchasing more expensive machinery rather than increasing the amount of machinery purchased. Despite numerous differences between Goolsbee (2004) and our paper, both find that not only is UIC (the price of machinery in Goolsbee (2004)) adjustment is important, it is also the only margin of adjustment in investment decisions for an average firm.

	Debt and Investment		Project-Cost Decomposition		
	ln(Total Debt)	ln(CAPEX)	ln(Project Cost)	ln(UIC)	ln(Capacity)
DRT	0.059***	0.041***	0.092**	0.103***	-0.011
	(0.017)	(0.013)	(0.041)	(0.017)	(0.026)
Controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	×	×	×
Product FE	×	×	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
R^2	0.819	0.874	0.702	0.832	0.827
Observations	2722	2675	3851	3851	3851

Table 4: The effect of DRT on total debt, investment, project cost, UIC, and capacity

This table reports the estimates of regressions 9 for debt and investment (firm-level regressions) and 10 for project cost, UIC, and capacity (product-level regressions). Total debt is the sum of both short and long-term debt. Investment is calculated using the balance sheet (= Δ PPE + Depreciation). Project cost = UIC$\times$ capacity. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the firm's headquarter state and year. The first two columns (firm-level regressions) have firm fixed effects, and the next three columns (product-level regressions) have product fixed effects. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

In Appendix I.3, we document that the subset of firm-years we are studying (firm-year in which the project is recorded as complete in that year) captures 82% of the total estimated effect of DRT on investment (the total estimated effect comes from using all firm-year observations in the Prowess dataset). This finding is important for two reasons. First, the sample used for the first column of Table I.3 is the sample of all firms in the Prowess dataset (4,423 firms). Thus, even though the primary sample of this paper (firms in Prowess with projects in CapEx) is a subset of the firms in Prowess, they account for most of the estimated effect of DRT on investment. Second, even in the subsample of firms with an investment project in CapEx, we only use the subsample of years for which a project in CapEx was recorded as "complete." Thus, 80% of the estimated coefficient comes from firm-years for which the firm completed a project in CapEx. This finding is consistent with prior literature's finding that investments are lumpy (see, i.e., Cooper and Haltiwanger (2006)), and thus, the bulk of the changes in PPE come from the years that the firm is investing in a project.

In Appendix I.3, we document that our results are similar if we use balance-sheet CAPEX to measure investment rather than the project cost, as well. The project-cost regression differs from the balance sheet-CAPEX regressions in two ways. First, the project cost is not the same as the balance-sheet CAPEX. Even though we document in Appendix B that these two variables are closely related, the findings in this table provide further evidence confirming our earlier results. Second, unlike balance-sheet CAPEX regressions in which the regression is run on a panel, project cost regressions are not a panel. Does this differences change the estimates? We use the non-panel regression setup used for project-cost regressions, but we substitute the project cost with balance sheet CapEx in years when the project was recorded as complete in the CapEx dataset. We find our results are the same, further confirming the consistency of these two measures.

5.3 Effect of DRT on TFP

The first two columns of Table 5 presents estimates of regression 9 for TFPR and TFPQ. Our estimates suggest that the establishment of DRTs increased the TFPR and TFPQ by 4.0% and 2.3%, respectively. These numbers are both statistically and economically significant.[52] Several recent articles study the effect of credit supply on productivity (Doerr, Raissi, and Weber (2018), Manaresi and Pierri (2018), Duval, Hong, and Timmer (2020), and Levine and Warusawitharana (2021)). Because the establishment of DRTs effectively increased debt availability, our findings are consistent with theirs.

5.3.1 Effect of DRT on TFPR components

Based on the decomposition of TFPR in subsection 3.3.1.1, a positive effect of DRT on TFPR can either come from an increase in revenue components (output quality, output price, and product scope), a decrease in cost components (labor, material input, and physical capital), or both. In this subsection, we study the effect of DRT on these variables.

[52]For instance, Topalova and Khandelwal (2011) document that a 10% decline in output tariffs on exporting in India led to a 0.32% increase in TFP. Considering that output tariffs between 1989 and 1996 declined, on average, by 54 percentage points implies the trade liberalization increased firm productivity by 1.7% through the channel of reduced output tariffs.

In columns 3-8 of Table 5, we document the effect of the introduction of DRT on output price, output quality, output quantity, sales share, and product scope for using product-level regression specification 10. Column 3 of Table 5 estimates the effect of the establishment of DRTs on output price. The establishment of DRTs increased output price by 2.8%. Although reducing prices in response to negative credit-supply shocks are documented in Kim (2021) and Lenzu, Rivers, and Tielens (2021), the proposed mechanism in our paper differs from theirs. Kim (2021) provides evidence consistent with the hypothesis that firms reduce prices to liquidate the inventory and generate additional cash flow from the product market to curtail the risk of financial distress. Lenzu et al. (2021) documents that constrained firms adjust prices and forgo short-run profits to generate the liquidity needed for expenditures on several productivity-enhancing activities such as $R\&D$ and and employee training programs.

Output quality discussed in 3.3.2 is not explicitly seen in the above decomposition, but as mentioned in the measurement section, higher quality is assigned to products with higher market shares conditional on price, and it is implicitly presented in the firm revenue. Column 4 gives the estimated effect on firm-output quality at the product level with model 10. The point estimate for the output quality of the DRT establishment laws is 3.8%. The point estimate for the output quantity of the DRT establishment laws is 2.5%, which might indicates an increment in capital utilization in treated firms considering that the level of capacity has not increased. In column 6, we show the DRTs establishment laws increase the sales at the product level by 5.2%. In the next section, we provide evidence consistent with the fact that firms increase the output quality through purchasing higher-quality capital. Column 7 indicates the number of products offered didn't change.

In columns 8-10 of Table 5, we document how the establishment of DRTs affects capital, labor, and material input. We estimate a specification similar to 9. The estimated coefficient shows the establishment of DRTs increased plants and machinery by 3.8%. Interestingly, in columns 9 and 10, we find no evidence that labor or material input cost has changed.

	Productivity		Revenue					Cost		
	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Quantity)	ln(Sales)	ln(# Products)	ln(PPE)	ln(Wage Bill)	ln(Material Expense)
DRT	0.040***	0.023**	0.028***	0.038***	0.025*	0.052**	0.016	0.038**	-0.015	-0.010
	(0.012)	(0.010)	(0.007)	(0.012)	(0.013)	(0.022)	(0.013)	(0.014)	(0.013)	(0.016)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product FE	×	×	✓	✓	✓	✓	×	×	×	×
Firm FE	✓	✓	×	×	×	×	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.556	0.537	0.912	0.873	0.917	0.923	0.739	0.714	0.757	0.775
Observations	2722	2619	1953	1953	1953	1953	2722	2722	2722	2722

Table 5: DRT, productivity, revenue, and cost

This table reports the estimates of regression 9 for productivity and cost (firm-level regressions) and regression 10 for revenue (product-level regressions). TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output quality derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. PPE measures the stock of physical capital. The wage bill includes all the different forms of compensation to employees (wages, bonuses, etc.). Material expense is the total payment for material inputs. Control variables are: log(total assets), log(PPE) (except PPE regression), wage bill/PPE (except wage bill regression), wage bill/sales (except wage bill regression). All regressions include fixed effects for the firm's headquarter state and year. The first two and the last three columns (firm-level regressions) have firm fixed effects, and columns 3-5 (product-level regressions) have product fixed effects. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

5.4 Heterogeneous Effect of DRT on UIC and Firm Productivity: Interactions with Scope for Quality Differentiation

In this subsection, we study whether our findings in the previous section are more pronounced for industries with higher scope for quality differentiation. As discussed in subsection 3.3.5 in more detail, studying the link between physical capital and output quality is important, especially in the context of a developing country such as India. If higher physical capital increases firm performance, we expect this effect to be more pronounced in industries with higher scope for quality differentiation. To test this hypothesis, we use ln(scope) and interact it with the DRT establishment dummy.

We use two regression specifications to study the interaction between scope for quality differentiation and DRT establishment. To study firm-level outcome variables (e.g., TFP), we use the following regression specification:

$$y_{ft} = \alpha_f + \alpha_t + \alpha_s + \beta_1 \times \mathrm{DRT}_{st} + \beta_2 \times \mathrm{DRT}_{st} \times H_{ft} + \lambda X_{ft-1} + \varepsilon_{ft} \tag{11}$$

The controls in this regression are the same as 9. The only difference is that the right-hand side has an interaction term $\beta_2 \times \mathrm{DRT}_{st} \times H_{lsft}$. To study product-level outcome variables (such as UIC), we use the following regression specification:

$$y_{lft} = \alpha_l + \alpha_t + \alpha_s + \beta_1 \times \mathrm{DRT}_{st} + \beta_2 \times \mathrm{DRT}_{st} \times H_{lft} + \lambda X_{ft-1} + \varepsilon_{lft} \tag{12}$$

The only difference between this regression and that of 11 is the fixed effects. In regression 11 we use firm-fixed effects (α_f), where in regression 12, we use product fixed effects (α_l) instead of firm fixed effects.

5.4.1 Heterogeneous Effects of DRT on UIC and Additional Capacity: Interactions with Scope for Quality Differentiation

Using the measures for scope for quality differentiation, $scope_{R\&D}$, we establish a link between project-cost components and quality consistent with the capital-quality hypothesis. Columns 1 through 3 of Table 6 indicate significant heterogeneity in the project-cost-components response using regression 12.[53] To facilitate interpretation, we have deviated the ln(scope) from its median prior to interacting it with DRT.

In column 1, the coefficient on DRT (uninteracted) reflects the impact of DRT in a sector with median values of the scope measure, which is 8.5%. The interaction coefficient documents the introduction of DRTs affects the UIC more in industries with higher scope for quality differentiation. Considering that the standard deviation of ln(scope$_{R\&D}$) is 1.3, DRT establishment increases UIC by $1.3 \times 0.072 + 0.085 = 17.7\%$ in an industry with a scope of one standard deviation above the median. In column 2, the coefficient on DRT (uninteracted) is -0.7%, and it is statistically insignificant, indicating no changes in additional capacity by introducing DRTs. The interaction coefficient documents that the introduction of DRTs affects the additional capacity more in industries with lower scope for quality differentiation. The establishment of a DRT increases additional capacity by $1.3 \times 0.021 + 0.007 = 3.3\%$ in

[53]In Appendix J, we estimate model specification 12 using $scope_{quality}$, and find similar results.

an industry with a scope of one standard deviation below the median. Column 3 documents a 7.1% increase in project cost by introducing DRTs, but the interaction coefficient is statistically insignificant. These results are consistent with the capital-quality-hypothesis in the trade-off between the UIC option and additional capacity. In industries with higher scope for quality differentiation, firms react to increased credit sources by purchasing higher UIC physical capital. In industries with lower scope for quality, firms react to increased credit by purchasing more additional capacity.

5.4.2 Heterogeneous Effects of DRT on Productivity and Its Components: Interactions with Scope for Quality Differentiation

Using the scope for quality differentiation, we now establish the link between the firm productivity, its components, and quality. In columns 4 to 10 in Table 6, we observe significant heterogeneity in the effect of DRTs introduction on firm productivity and its component by estimating regressions 11 and 12. Consistent with the predictions of the capital-quality channel, the differential increase of UIC translates into differential firm TFP and its components' response.

In column 4 of Table 6, we show output price increases more in industries with higher scope for quality differentiation. More specifically, a firm that belongs to an industry with one-standard-deviation higher scope above the median has $0.018 \times 1.3 + 0.020 = 4.5\%$ higher output price. In column 2, we document that output quality increases more in industries with higher scope for quality differentiation. The firm that belongs to an industry with one-standard-deviation higher scope above the median has $0.027 \times 1.3 + 0.029 = 6.4\%$ higher output quality. Consistent with column 5 of Table 6 and the fact that the additional capacity increased more in industries with lower scope for quality differentiation, in column 6, we find that output quantity increases more in industries with lower scope for quality differentiation. This fact is consistent with the physical-capital quality channel. In column 7, we estimate a more intense impact in sales share in industries with higher scope for quality differentiation in response to the introduction of DRTs, consistent with the physical-capital quality story.

Column 8 finds no change in the number of products offered for treated firms in industries with higher scope for quality differentiation. In column 9, we document that TFPR increases more in industries with higher scope for quality differentiation. More specifically, a firm that belongs to an industry with one-standard-deviation higher scope above the median has $0.027 \times 1.3 + 0.030 = 6.5\%$ higher TFPR. Column 10 provides no increment in TFPQ in industries with more scope for quality differentiation.

	Project-Cost Decomposition			Revenue					Productivity	
	ln(UIC)	ln(Capacity)	ln(Project Cost)	ln(Price)	ln(Quality)	ln(Quantity)	ln(Sales)	ln(# Products)	ln(TFPR)	ln(TFPQ)
DRT	0.085***	-0.014	0.071**	0.020***	0.029**	0.034*	0.055**	0.009	0.030**	0.025**
	(0.023)	(0.023)	(0.034)	(0.006)	(0.011)	(0.018)	(0.024)	(0.021)	(0.013)	(0.011)
DRT×ln(scope$_{R\&D}$)	0.072**	-0.021**	0.058	0.018**	0.027**	-0.010	0.011*	0.014	0.027**	0.008
	(0.029)	(0.010)	(0.055)	(0.008)	(0.011)	(0.009)	(0.006)	(0.010)	(0.008)	(0.014)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	×	×	×	×	×	×	×	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	×	×	×
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.837	0.831	0.702	0.913	0.874	0.935	0.924	0.740	0.557	0.538
Observations	3851	3851	3851	1953	1953	1953	1953	2722	2722	2619

Table 6: Heterogeneous effect of DRT: Interaction with scope for quality differentiation

This table reports the estimates of regression 11 for productivity and #products (firm-level regressions) and 12 for project-cost decomposition, price, quality, quantity, and sales share (product-level regressions). scope$_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln(scope$_{R\&D}$) has been deviated from sample median. Project cost = UIC × capacity. Output quality derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the firm's headquarter state and year. Productivity and #products (firm-level regressions) regression include firm-fixed effects. Project-cost decomposition, price, quality, quantity, and sales share (product-level regressions) include product-level fixed effects. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

5.5 Heterogeneous Effects of DRT: Interactions with Measures of Financial Constraints

In this subsection, we study whether the effect of DRT is stronger for firms that are potentially more financially constrained. If DRT alleviates financial constraints, we expect the result to be stronger for industries and firms that are more financially constrained. We study the interaction of DRT with four different measures of financial constraints: (1) firm size,

(2) two-digit NIC industry leverage, (3) two-digit NIC industry (Rajan and Zingales (1998)) measure of external financial dependence, (4) firm's age. For brevity, we focus on the heterogeneous treatment effects on UIC and TFPR, the two main outcome variables of interest. Columns 1 and 2 of Table 7 document the interaction of DRT with a dummy variable for size. Smaller firms are known to be more financially constrained (see i.e., Hadlock and Pierce (2010)). We sorted firms based on their size in 1994. H_{it} is equal to one if the firm belongs to the lower 50% of the distribution of firm size in 1994, and zero otherwise. Columns 1 and 2 show that the effect of DRT on UIC and TFPR is higher for smaller firms.

Columns 3 and 4 of Table 7 document the interaction of DRT with a dummy variable for industry leverage. We sorted two-digit NIC industries based on mean industry leverage (debt/assets). H_{it} is equal to one if the firm belongs to an industry in the top 50% of the distribution of industry leverage in 1994, and zero otherwise. Columns three and four show the effect of DRT on UIC and TFPR is higher for firms that belong to industries with higher leverage.

Columns five and six of Table 7 document the interaction of DRT with a dummy variable for Rajan and Zingales (1998) measure of external financial dependence. We sorted industries based on the two-digit NIC industry (Rajan and Zingales (1998)) measure of external financial dependence in 1994. H_{it} is equal to one if the firm belongs to an industry in the top 50% of the distribution of external financial dependence, and zero otherwise. Columns 5 and 6 show the effect of DRT on UIC and TFPR is higher for firms more dependent on external finance.

Columns 7 and 8 of Table 7 document the interaction of DRT with a dummy variable for size. Common knowledge suggests younger firms are more financially constrained (see, i.e., Hadlock and Pierce (2010)). We sorted firms based on their age in 1994. H_{it} is equal to one if the firm belongs to the lower 50% of the distribution of firm age in 1994, and zero otherwise.[54] Even though the interaction coefficient for age is not statistically significant, it is economically meaningful. The sign is also positive, consistent with younger firms investing in higher UIC capital and increasing TFPR more.

[54]On average, a young firm was 4.7 years old in 1995.

Heterogeneity	Small Firm		High Industry Leverage		RZ Industry Measure		Young Firm	
Variable	ln(UIC)	ln(TFPR)	ln(UIC)	ln(TFPR)	ln(UIC)	ln(TFPR)	ln(UIC)	ln(TFPR)
DRT	0.089***	0.031**	0.086***	0.032***	0.090***	0.027**	0.097***	0.029***
	(0.021)	(0.013)	(0.029)	(0.012)	(0.027)	(0.011)	(0.020)	(0.010)
DRT$\times H_{it}$	0.037*	0.017**	0.027*	0.013*	0.026**	0.016**	0.022	0.015
	(0.020)	(0.007)	(0.015)	(0.007)	(0.012)	(0.007)	(0.016)	(0.010)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Product FE	✓	×	✓	×	✓	×	✓	×
Firm FE	×	✓	×	✓	×	✓	×	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.831	0.559	0.832	0.559	0.833	0.557	0.832	0.558
Observations	3694	2615	3851	2722	3851	2722	3851	2722

Table 7: Heterogeneous effects of DRT on debt, UIC, and TFP: Interactions with measures of financial constraints

This table reports the heterogeneous effect of DRT on UIC using regression 12 (product-level regression) and TFPR using regression 11 (firm-level regression). Dummy variable H_{it} is equal to one if the firm belongs to the 50% of firms that are more financially constrained. For columns 1 and 2, H_{it} is equal to one if the firm size is less than the median (based on the value of assets in 1994). For columns 3 and 4, H_{it} is equal to one if the firm belongs to an industry with above-median leverage (debt over assets). For 5 five and 6, H_{it} is equal to one if the firm belongs to an industry with the above-median Rajan-Zingales external financial-dependence measure. For columns 7 and 8, H_{it} is equal to one if the firm age is below the median. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the firm's headquarter state and year. Regressions for TFP include firm fixed effects (firm-level), and regressions for the UIC include product fixed effect (product-level). Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

6 Alternative Explanations

The establishment of DRTs increased TFP and UIC of investments for firms in treated states. One explanation for these findings is that TFP in treated states increased because firms invested in higher UIC physical capital.[55] However, the establishment of DRTs might have affected firm-level TFP through other channels, as well. We conduct several tests to investigate the potential relevance of other channels in explaining our findings.

[55]In Appendix I.4, we use the establishment of DRTs as an instrument variable for UIC to provide reduced-form estimates of the effect of UIC on firm outcomes. The evidence provided so far seems to suggest that this assumption is likely to hold. However, the IV estimates need to be taken with a grain of salt.

First, we directly test for three specific mechanisms: increased R&D, increased training of employees, and increased intangible investment. Second, we focus on price, quality, and sales share for products without investment projects in the subsample of multi-product firms. If investment in physical capital explains our findings, we expect the change in price, quality, and sales share to be insignificant for this subsample. Third, we test whether the alternative explanations discussed so far are stronger in industries with higher scope for quality differentiation. Fourth, we focus on a subsample of projects in which the firm headquarter state is treated, but the project location is not treated. Lastly, we interact DRT with several measures of competition in the physical-capital seller market to study the relevance of explanations that rely on markup differences across physical-capital suppliers. We describe how these tests are conducted in the following subsections and what potential alternatives they address.

6.1 Three Specific TFP Increasing Mechanisms

The goal of this subsection is to study whether three specific mechanisms documented in recent research articles (see, i.e., Huber (2018), Anzoategui, Comin, Gertler, and Martinez (2019), Garcia-Macia (2017), Manaresi and Pierri (2018), Duval et al. (2020), and Lenzu et al. (2021)) can explain the relationship between DRT and TFP. These articles provide evidence that firms that face a reduction in credit supply reduce R&D or employee training programs or intangible investment. Consequently, reduced R&D, employee training programs, and intangible investment may lower productivity.

6.1.1 R&D and Employment Training Programs

Columns 1 and 2 of Table 8 show the results of regression 9 and 11 for R&D expenses. The estimated coefficient in column one is not statistically significant.[56] Furthermore, it is economically small: the estimated coefficient is less than 0.1% of the standard deviation of R&D. Furthermore, the interaction coefficient for scope for quality differentiation is neither statistically nor economically significant either.

The small interaction coefficient is important for another reason. Increased TFP is

[56] R&D information is mostly non-missing for larger firms in Prowess. Because our sample mostly includes large firms, the R&D information is non-missing for about 60% of the sample.

stronger in industries with higher scope for quality differentiation. Thus, we expect any potential explanation to be stronger in these industries, as well. Thus, R&D does not seem to be a potential explanation for our findings.

Columns 3 and 4 of Table 8 show the results of regression 9 and 11 for employee training expenses. The estimated coefficient in column three is not statistically significant. It also has the "wrong" sign; that is, firms in treated states reduced employee training expenditures. The coefficient is economically small: it is less than 0.2% of the standard deviation of employee training expenses. Furthermore, the estimated coefficient for the interaction term in column 4 is also not statistically significant. Thus, employee training does not seem to be a potential explanation for our findings.

6.1.2 Intangible Investment

Columns 5 and 6 of Table 8 show the results of regression 9 and 11 for intangible investment. We follow Peters and Taylor (2017) and construct a measure of intangible investment using the firm's R&D plus 30% times SG&A (selling, general, and administrative) spending.[57] Column 5 shows the estimated coefficient is not statistically significant. The coefficient is economically small: it is less than 0.2% of the standard deviation of intangible investment. Column 6 shows the interaction coefficient with scope for quality differentiation is not statistically significant either. Thus, intangible investment does not seem to be a potential explanation for our findings.

[57]We also used a different measure of intangible investment: the logged value of the net change in the balance-sheet intangibles following Duval et al. (2020). We find similar results using that measure.

	R&D expenses		Training Expenses		Intangible Investment	
	(1)	(2)	(3)	(4)	(5)	(6)
DRT	0.005	0.002	-0.003	-0.004	0.013	0.007
	(0.135)	(0.121)	(0.107)	(0.097)	(0.044)	(0.039)
DRT × ln(scope$_{R\&D}$)		0.003		0.004		-0.003
		(0.067)		(0.122)		(0.044)
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.571	0.572	0.612	0.612	0.549	0.550
Observations	1837	1837	1036	1036	1789	1789

Table 8: Effect of DRT on R&D, employee training expenses, and intangible investment

This table reports the estimates of regression 9 (for columns 1, 2, and 5), and 11 (for columns 2, 4, and 6). scope$_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln(scope$_{R\&D}$) is shifted to have a median of zero. Intangible investment is defined as the sum of R&D and 0.3 × SG&A following Peters and Taylor (2017). Controls include: log(PPE), log(total assets), wage bill/PPE, wage bill/sales. All regressions include fixed-effects for year, firm's headquarter state, and firm. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

6.2 Effect of DRT Establishment on Products without an Investment Project

This subsection tests whether treated firms' output price, output quality, and sales share changed for the product categories for which the firm did not have an investment project in CapEx. If physical capital is indeed important in increasing price, output quality, and sales share,[58] we would expect the estimated coefficients for these variables to be meaningful only for the subset of products with an investment project in CapEx. However, an alternative

[58]Ideally, we would want to do this exercise for different components of TFP; however, we are limited by the outcome variables for which we have disaggregated product category data, namely, price, quality, sales share.

explanation, such as increased R&D, does not explain why price, quality, and sales share should only increase for products with an investment project.

In this subsection, we limit the sample to products without an investment project in CapEx. More specifically, for a firm f that had an investment project in product j at time t, we use price, output quality, and sales-share variables for all products k sold by firm f in year t, where $k \neq j$. The estimated coefficient for the unit price is not statistically significant.

Columns 1 and 2 of Table 9 show the results of regression specification 10 and 12 for output price. Furthermore, column 2 documents that the estimated coefficient for scope for quality differentiation is not statistically significant either. The estimated coefficient for the unit price is not statistically significant.

Columns 3 and 4 of Table 9 show the results of regression specification 10 and 12 for output quality in the subsample of products for which firms did not have an investment project in CapEx. The estimated coefficient for the output quality is not statistically significant. Furthermore, column 4 documents that the estimated coefficient for scope for quality differentiation is not statistically significant either. Columns 5 and 6 of Table 9 show the results of regression specification 10 and 12 for sales share in the subsample of products for which firms did not have an investment project in CapEx. The estimated coefficient for sales share is not statistically significant. Furthermore, column 6 documents the estimated coefficient for scope for quality differentiation is not statistically significant either.

These finding are important for two reasons. First, any potential explanation for our findings should explain why price, output quality, and sales share increased in treated states, but only for the products for which the firm had an investment project in CapEx. Second, it suggests that scope for quality differentiation is not merely capturing differences in price, quality, sales-share sensitivity to debt availability across different industries. If it were, we would have expected the price, output quality, and sales share interactions to be significant for products without an investment project, as well.

	ln(Output Price)		ln(Output Quality)		ln (Sales Share)	
	(1)	(2)	(3)	(4)	(5)	(6)
DRT	0.005	0.004	0.008	0.007	0.008	0.006
	(0.013)	(0.014)	(0.015)	(0.016)	(0.018)	(0.019)
DRT $\times$ ln(scope$_{R\&D}$)		0.004		0.005		0.005
		(0.011)		(0.019)		(0.017)
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.873	0.874	0.853	0.853	0.817	0.817
Observations	4491	4491	4491	4491	4491	4491

Table 9: Effect of DRT on output price, output quality, and sales share for subsample of products for which firms did not have an investment project in CapEx

This table reports the estimates of regression 10 (for columns 1, 3, and 5) and 12 (for columns 2, 4, and 6). We focus on the subsample of products that firms did not have an investment project in CapEx. More specifically, for a firm f that had an investment project in product j at time t, we use price, quality, and sales-share variables for product k sold by firm f in year t, where $k \neq j$. scope$_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln(scope$_{R\&D}$) is shifted to have a median of zero. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed-effects for year, firm's headquarter state, and product category. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

6.3 Projects of Treated Firms in Non-Treated States

In this subsection, we study the effect of DRT on the subsample of projects in which the project location is not treated. Consider the following alternative explanation. The reform could have led to an increased value of land in treated states. The increased value of land might have made an investment in those states more expensive. Thus, an increased UIC for firms in treated states might be unrelated to these firms' acquiring more productive physical capital. To assess the validity of such an explanation, we focus on the sub-sample of projects in which the project location is not a treated state. The estimate of the coefficient of interest comes from comparing firms headquartered in a treated state versus those headquartered in a non-treated state. If the alternative explanation is valid, we expect to find no effect for UIC in this sub-sample. However, if our explanation is valid, we expect to find significant differences between the two groups of firms in this sub-sample.

Columns 1 and 2 of Table 10 show the results of regression specifications 10 and 12 for UIC in the sub-sample of projects in which the project location is not treated, respectively. Column 1 estimates suggests that firms in treated states increased UIC even though the project was located in a non-treated state. Furthermore, the increase was more pronounced in industries with more scope for quality differentiation. Columns 3 and 4 of Table 10 show the additional capacity did not change significantly for treated firms. Columns 5 and 6 show the project cost increased more for firms in treated states. Overall, these findings suggest the firm's headquarter location drives the results, not the location of the project.

	ln(UIC)		ln(Capacity)		ln(Project Cost)	
	(1)	(2)	(3)	(4)	(5)	(6)
DRT	0.063**	0.056**	0.034	0.025	0.098**	0.082*
	(0.024)	(0.021)	(0.031)	(0.029)	(0.043)	(0.046)
DRT × ln($\text{scope}_{R\&D}$)		0.046**		-0.024		0.022
		(0.021)		(0.017)		(0.031)
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.722	0.722	0.698	0.699	0.573	0.574
Observations	1013	1013	1013	1013	1013	1013

Table 10: Effect of DRT on project cost components in the sub-sample of projects where the project location is in a non-treated state

This table reports the estimates of regression 10 (for columns 1, 3, and 5) and 12 (for columns 2, 4, and 6). We focus on the subsample of projects in which the project location is a non-treated state (without a DRT establishment). Project cost = UIC × capacity. $\text{scope}_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln($\text{scope}_{R\&D}$) is shifted to have a median of zero. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the year, firm's headquarter state, and product category. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

6.4 Market Power in the Physical-Capital Market

In this subsection, we study whether the establishment of DRTs increased UIC more in less competitive physical-capital suppliers market. UIC is the unit price of physical capital. The price of physical capital is by definition equal to the marginal cost of its production times markup. If the marginal cost of producing a physical capital is high, it is likely because of higher quality. However, if the differences in the prices of physical-capital come from differences in markups across sellers, we would observe differences in UIC that may not be related to differences in marginal cost. Markups are lower in more competitive industries. Thus, if differences in markups can explain our findings, we expect UIC to increase more substantially in industries with less competition in the physical-capital seller markets.

We construct four different competition measures in the physical capital seller market and study its interaction with DRT establishment. To construct the first measure, we take the following steps: First, we match each project to a three-digit NIC code. Second, for a project matched to a three-digit NIC code, j, we use the input-output matrix (provided by the Ministry of Statistics and Program Implementation by the Government of India) to construct, α_{ij}, the share of input from industry i for industry j.[59] Third, we calculate the Herfindahl-Hirschman Index (HHI) of industry i from the universe of firms in the Prowess dataset and use the input-output matrix weights α_{ij} to construct a measure of competition in the physical-capital seller market.

$$HHI_{IO}(j) = \sum_{i \in \text{physical capital}} \alpha_{ij} HHI_i \tag{13}$$

Our second, third, and fourth measure of competition in physical-capital seller markets follow: (2) $HHI_{\text{contractor}}$ is the inverse number of contractors in each four-digit industry NIC code, (3) $HHI_{\text{consultant}}$ is the inverse number of consultants in each four-digit industry NIC code, and (4) $HHI_{\text{machinery suppliers}}$ is the inverse number of machinery suppliers in two-digit industry NIC code.[60,61] For each project CapEx provides information about

[59]We use the 2007 version of the input-output table because it covers more industries relative to the previous versions. Furthermore, the input-output table is not at the three-digit NIC industry for every industry. We aggregate to the three-digit NIC industry level.

[60]If each contractor has an equal share, the inverse of the number of contractors is equal to the HHI.

[61]We define the machinery-supplier measure at each two-digit industry to have enough observations for each industry because only 12% of projects have information on machinery suppliers.

the project associates. Each project-associate can take one of several roles including "contractor," "consultant," "machinery supplier," and so on.[62] Furthermore, CapEx provides a unique identifier for each project associate. We use the project-associate information in CapEx to construct the three measures of competition in physical-capital seller market. The standard deviation of HHI_{IO}, $\text{HHI}_{\text{contractor}}$, $\text{HHI}_{\text{consultant}}$ and $\text{HHI}_{\text{machinery-supplier}}$ is 0.06, 0.20, 0.23, and 0.15, respectively.[63]

Each of the measures used here has its shortcomings. HHI_{IO} is a measure of competition in the input market, and not specifically the physical-capital seller market. Even though $HHI_{\text{contractor}}$ and $HHI_{\text{consultant}}$ are not directly related to the competitiveness of machine suppliers, they capture competition in services and logistics needed to implement the projects.[64] Because UIC includes these costs for the projects, if the market power hypothesis is deriving our results, we might expect to see a higher UIC in less competitive industries. Despite the shortcomings of different measures, we believe together they are useful in understanding competition in the physical-capital seller market.

Table 11 reports the result of regressions specification 12, where the interaction term is one of the four different measures of competition in the physical-capital seller market described above. Column 2 reports estimates of the interaction term with HHI_{IO}. The coefficient is statistically insignificant. Furthermore, it is economically small, because a one-standard-deviation increase in HHI_{IO} increases the estimated effect by $0.06 \times 0.61 = 0.004$, which is 4% of the average effect of DRT establishment on UIC. Columns 3, 4, and 5 are similar, as well. The interaction term is statistically insignificant and economically small. Furthermore, in column 5, the interaction term has the "wrong" sign, implying that an

[62]Several other firms are involved in the implementation of a typical project. They include civil contractors, machinery suppliers, non-financial consultants, and so on. The names of these agencies, their role in the project, and the contract value, if available, are captured by CapEx. According to CapEx, the primary sources to capture this information are public sources, contractor and consultant firms' websites, and platforms. CapEx also contacts the contractor and consultant firms to get such information. Based on this information, we believe the set of contractors and consultants for a project is nearly complete, although we don't have full details on machinery suppliers of projects.

[63]We use a larger set of projects for constructing these measures that consist of about 12,000 projects. About 8,000, 5,000, and 1,500 of these projects have information about contractors, consultants, and machinery suppliers. Overall, the data contain about 1200, 800, and 300 unique contractors, consultants, and machinery suppliers. Furthermore, the data contain 125 and 75 different four-and three-digit NIC industries.

[64]The contractor's responsibilities are not limited to the construction of property needed in projects. Some contractors are also involved in purchasing and installing the machinery required to implement the projects.

increase in $HHI_{\text{machinery suppliers}}$ is associated with a decrease in UIC. To sum up, our empirical findings do not support the hypothesis that market power in the physical-capital market can explain our results.

	ln(UIC)				
DRT	0.103***	0.091***	0.092***	0.097***	0.088***
	(0.017)	(0.021)	(0.029)	(0.032)	(0.027)
DRT× HHI_{IO}		0.061			
		(0.123)			
DRT× $HHI_{\text{contractor}}$			0.025		
			(0.073)		
DRT× $HHI_{\text{consultant}}$				0.043	
				(0.054)	
DRT× $HHI_{\text{machinery suppliers}}$					-0.012
					(0.097)
Controls	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
R^2	0.832	0.833	0.832	0.833	0.833
Observations	3851	3768	3851	3851	3851

Table 11: Interaction with measures of market power in the physical-capital supplier market

This table reports the estimates of the DRT establishment on UIC using regression specification 12 (product-level regression). HHI_{IO} is derived from equation 13. $HHI_{\text{contractor}}$ is the inverse of the number of distinct contractors at the four-digit NIC level. $HHI_{\text{consultant}}$ is the inverse of the number of distinct consultants at the four-digit NIC level. $HHI_{\text{machinery suppliers}}$ is the inverse of the number of distinct machinery suppliers at the two-digit NIC level. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the year, firm's headquarter state, and product category. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

In Appendix K, we show that UIC is positively correlated with the import of physical capital. The international trade literature shows the average quality of imported goods is higher than that of domestic goods in developing countries. Thus, the positive correlation between UIC and physical-capital import provides further evidence consistent with higher-UIC capital having higher quality.

7 Conclusion

In this paper, we provide novel evidence measuring the quality of physical capital and linking higher quality of capital to higher productivity and higher output quality. We show that financial frictions can explain the choice of lower physical-capital quality, and consequently, lower productivity. To measure the quality of physical capital, we exploit a novel Indian project-level investment dataset, in which we measure physical capital quality as the project cost divided by the additional capacity.

Some interesting questions remain unanswered. Higher physical-capital quality can substitute for labor. But does it? The benefit of having data on physical-capital quality at the firm-product-level is that this question can be studied at a finer level. The presence of financial constraints is one important explanation for variation in capital quality, but it may not be the only one. Understanding what other factors can affect physical-capital quality would be important. For instance, does increased competition or access to foreign markets induce firms to choose higher-quality capital?

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A Data Details

This appendix provides further details about CapEx dataset. The dataset is collected from multiple sources including the annual reports of firms, media reports, government agencies, company websites, promoter's website, and project contractors.[65] Furthermore, data are also collected through direct contact with companies engaged in executing the projects.

CapEx also includes data on the status of projects over time. Each project has an announcement date.[66] After the initial announcement, the data vendor keeps track of the project throughout its life until the project is either completed or abandoned.[67] Projects are discontinued for various reasons. Over the sample period, 1995-2003, around 63% of projects become complete. The rest are either abandoned (5%), stalled (8%), have no information available (8%), or have an ongoing status (16%). In addition to private firms, the dataset includes information about investment projects undertaken by states or central governments.

The definition of a project can be somewhat arbitrary. An investment project can consist of several investment projects done in different locations or at different stages.[68] As a rule of thumb, CMIE records components of "one" project as separate projects if it can obtain separate cost data for each component or if the company treats them as separate projects. We use the definition of CMIE to identify a project.[69] Ninety-nine percent of projects create capacity to produce in a single-product category.[70]

Capacity is rarely used in academic articles, but capacity utilization, the ratio, has been used in several research articles to explain business-cycle patterns (i.e., Greenwood, Her-

[65]Note that whenever an inconsistency exists between different sources CapEx doesn't consider the project.

[66]The project cost is not determined at the date of the announcement for all projects.

[67]CMIE calls firms that undertake the projects to follow up on the status of projects based on a defined schedule. CMIE asks firms whether a change in project has occurred characteristics and timing. We have detailed information about the timing of calls, whether firms respond to CMIE, and information about projects if they changed the project characteristics.

[68]About 1.5% of the projects in CapEx have more than one phase.

[69]The main results would hold if we treated all projects undertaken by the firm to produce one product in a single year as one project.

[70]We drop the other 1% because calculating UIC when the project involves multiple product categories is impossible.

cowitz, and Huffman (1988)). The U.S. Census Bureau surveys plant capacity in the U.S. using the Quarterly Survey of Plant Capacity Utilization. This data-collection effort has started from 1967 and continues to date.

Capacity added to the firm might be measured in different units, even for the same product category. For instance, projects for the production of sunflower oil might record capacity in "Tonnes Per Day" or "Kg Per Day." We manually convert measurement units to a standard format for each product category whenever possible. For some products, this conversion is not possible. For instance, a project to produce polyester yarn might be recorded in "Tonnes" or "Spindles." We consider products in the same product category with different measurement units as distinct products. In other words, we define each unique product code and measurement-unit pair as a distinct product.[71]

Table A.1 is a sample project in the CapEx dataset. The project was undertaken by company "Valson Industries Ltd." It was announced in January 1997 and completed in March 1997, and cost 124 million Indian rupees. The project is located in Gujarat and adds a total capacity of 1.8 tonnes for the annual production of polyester yarn to the company.

Company	Product	Product code	Announcement	Completion	Cost
Valson Industries Ltd	Polyester Yarn	36200808160000000000	January 1997	March 1997	124 Million INR
State of Completion	**District**	**New Capacity**	**Unit**	**Type**	**Industry**
Completed	Valsad	1.8	'000 Tonnes	Substantial Expansion	Man-made filaments & fibres

Table A.1: A Sample Project

This table presents some of the information available in the CapEx dataset for a sample project undertaken by the company "Valson Industries Ltd.".

B Cross-Validation of CapEx with Prowess Dataset

This section shows the total project cost closely follows its firm-level balance sheet counterpart (changes in PPE plus depreciation) both in the time series and cross-section. Furthermore, we cross-check the capacity variable in the Prowess dataset (for the subset of firm-products this variable is available) with the variable from CapEx and find these two

[71] For less than 2% of the projects, we can't convert measurement units to get a single measurement unit for one product category.

variables are broadly consistent. As a final check, we show the additional capacity variable in the CapEx dataset is consistent with the sales-quantity variable reported in the Prowess dataset.

B.1 Project Cost and Balance-Sheet CAPEX

We use the term "balance-sheet CAPEX" to refer to the widely used variable derived from balance-sheet data for measuring firm-level investment:

$$\text{Balance-Sheet CAPEX} = \text{changes in PPE} + \text{depreciation}$$

First, we check if the variable total project cost, which measures how costly it is for the firm to undertake a project, follows the widely used measure of the firm-level investment, that is, balance-sheet CAPEX. To do so, we compare the sum of the project cost at the firm level "(sum project cost hearafter)", with balance-sheet CAPEX. The project costs in CapEx can be categorized into four groups: (1) cost of purchasing machinery and equipment, (2) cost of purchasing land and construction equipment for making plants, (3) cost of hiring workers to install machinery and build a plant, and (4) cost of purchasing the license to start a new product. We expect the sum project cost and balance-sheet CAPEX to be different for several reasons. First, CapEx doesn't include all projects undertaken by firms; the projects in the CapEx dataset are projects that cost more than 10 million rupees. Furthermore, not all investment made by firms add more capacity to the firm, which is a criterion inclusion in the CapEx dataset. Second, some projects take more than one year to complete. For these projects, we assume that the total project cost is spread equally over the life of the project. However, how this variable is reflected in balance-sheet CAPEX is unclear. Third, although most of the projects in CapEx become complete at some point, some projects are abandoned or stalled or we don't have reliable information about them. We chose to drop these projects.[72] However, whether these projects are partially reflected in balance-sheet CAPEX is unclear. Fourth, in derivation of balance-sheet CAPEX in accounting, it is usually assumed that the value of the asset depreciates uniformly through the life cycle of

[72] A variable in CapEx indicates the status of the project: Completed, Stalled, Abandoned, or No Information.

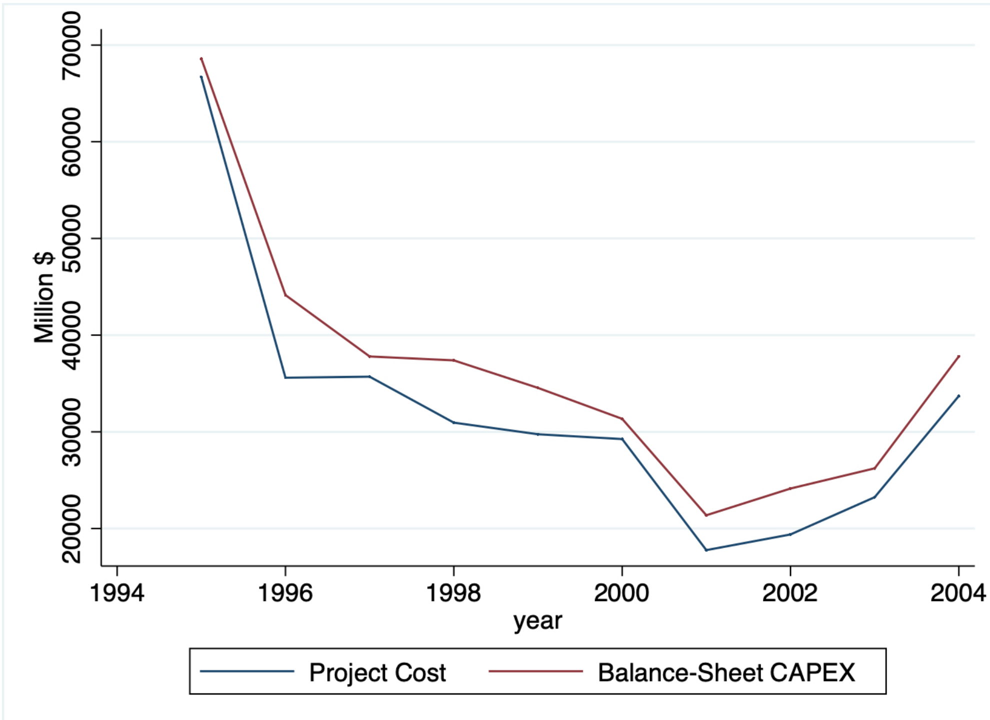


Figure B.1: Time-series of the total project costs and balance-sheet CAPEX

This figure plots the time-series of the total project costs (from CapEx) and balance-sheet CAPEX (from Prowess) for the sub-sample of firm-year observations with positive project costs from 1995 to 2004. Balance-sheet CAPEX is measured as the change in PPE+depreciation.

the asset.[73] Any deviation from this predetermined assumption could result in the difference between the sum project cost and balance-sheet CAPEX.

(I) Time-series aggregate of balance-sheet CAPEX (from Prowess dataset) and total project cost (from CapEx dataset): In Figure B.1, the aggregate level of balance-sheet CAPEX and sum project costs are plotted from 1995 to 2004. For this plot, to have a fair comparison, we exclude firm-year observations without a CapEx investment project from 1995 to 2004. The graph illustrates that these two measures track each closely over time.

(II) Cross-sectional correlation of firm-level balance-sheet CAPEX (from Prowess dataset) and total project cost (from CapEx dataset): We exclude firm-year observations without a CapEx investment project. To see how the sum project cost is correlated with balance-sheet

[73]Note that life of the asset is assumed ex-ante for deriving the depreciation in balance-sheet.

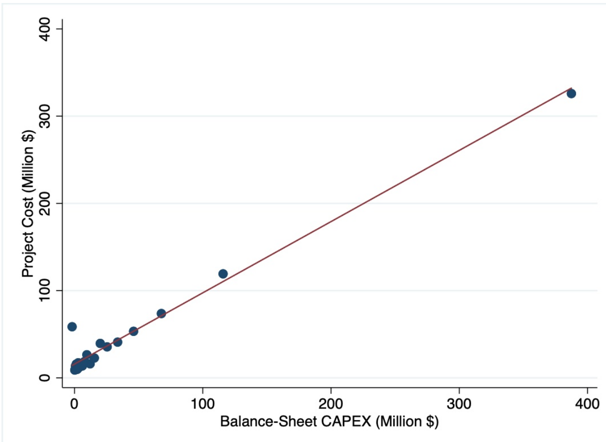
CAPEX, we run the following regression:

$$\text{Sum Project Cost}_{ft} = \beta \times \text{Balance-Sheet CAPEX}_{ft} + \epsilon_{ft} \tag{B.1}$$

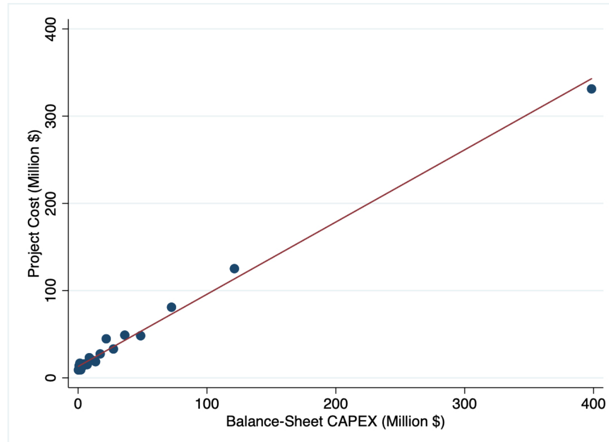
The results of the regression are in Table B.1. The first column provides the result for the sample with a positive the sum project cost. The coefficient is 0.854 and strongly rejects the hypothesis that sum project cost is not related to balance-sheet CAPEX. The test rejects the equality of the two measures; however, R^2 of the regression is 0.645, which indicates a strong correlation of 0.80 between investment and total project cost.[74] One reason for the potential deviation between these two variables could be the negative balance-sheet CAPEX. To check that, we drop investments with a negative amount, which account for around 1% of the sample, and we see the result in column 2. The coefficient becomes larger by around 3%. The correlation also becomes stronger, at 0.82. These facts are consistent with the validity of sum-project-cost data. Another reason for the potential deviation between these two variables could be the fact that some projects last more than one year, and the cost could be reflected unequally within years of implementation. In column 3, we only consider a firm-year sample that involves only one project. This focus could remove a potential bias between the two measurements. Both the coefficient and correlation become larger. The coefficient increases significantly to 0.894. The R^2 is 0.714, which indicates the correlation of 0.85 between the two measures.

To show the relationship between project costs and balance-sheet CAPEX at the firm level visually, we plot the binscatter of these variables. binscatter of sum project cost and balance-sheet CAPEX is depicted in Figure B.2. The left-hand-side figure is the binscatter for the sample with A positive-sum-project cost. We drop the sample with negative balance-sheet CAPEX, and the result is shown for the rest of the sample in the right-hand-side figure.

[74]In case of equality, we expect $\beta = 1$.



(a)



(b)

Figure B.2: Binscatter plot for firm-year balance-sheet CAPEX vs. the firm-year project cost

(a) This figure is the binscatter plot for firm-year balance-sheet CAPEX (from Prowess dataset) vs. the firm-year project cost (from CapEx dataset). (b) This figure is the binscatter plot of firm-year balance-sheet CAPEX (from Prowess dataset) vs. the firm-year project cost (from CapEx dataset) for the sub-sample of firm-year observations with positive balance-sheet CAPEX.

	CAPEX		
	(1)	(2)	(3)
Sum Project Cost	0.854***	0.873***	0.898***
	(0.015)	(0.014)	(0.018)
R^2	0.634	0.671	0.728
Observations	2722	2675	2312

Table B.1: Balance-sheet CAPEX and project cost for firm-year observations

This table reports the estimates of regression B.1. We exclude firm-year observations without the CapEx investment project. The sum project cost is the sum of all project cost at the firm-year level. Balance-sheet CAPEX is defined as changes in PPE + depreciation. In column 2, we exclude firm-year observations with negative balance-sheet CapEx. In column 3, we exclude firm-year observations with projects that last more than one year. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

B.2 Additional Capacity (from CapEx)

I. Relationship with capacity (from Prowess) Firms in India are not required to report production capacity. However, some firms report production capacity in their annual report. Suppose CapEx's new capacity information is accurate. In that case, a substantial correlation must exist between the additional capacity variable from CapEx and differences in production capacity for firms that have reported their production capacity. Because we only consider completed projects and we only observe project costs whose size is more than a threshold, we don't expect a full correlation between these two variables. To see how these two variables are related, we run the following regression at the product level:

$$\Delta\text{Capacity (from Prowess)}_{lt} = \alpha + \beta\text{Additional Capacity (from CapEx)}_{lt} + \epsilon_{lt} \qquad \text{(B.2)}$$

The left-hand side of the regression is the change in the capacity, and the right-hand side is the additional capacity from CapEx.[75] Table B.2 reports the results of the regression B.2. In the sample period, we can only recover 30% of the change in capacity from the reported capacity. Note three important facts regarding the regression. First, the intercept is not significantly different from zero. Second, the main coefficient is not significantly different from 1. Third, the R^2 of the regression is 0.807, which indicates a correlation of 0.90 between two variables. These three facts provide strong evidence that the additional capacity variable in the CapeX tracks the corresponding variable closely in Prowess for the sub-sample of reported capacity.

[75] We only consider firms that have reported the capacity for at least three years in our sample.

	Δ Capacity at Prowess
Additional Capacity at CapEx	1.04***
	(0.07)
Constant	-0.06
	(0.05)
R^2	0.807
Observations	1202

Table B.2: Production capacity change (from Prowess) vs. additional capacity (from CapEx)

This table reports the estimations of regression B.2, where the left-hand-side variable is the change in production capacity (from Prowess), and the right-hand-side variable is the project's reported additional capacity (from CapEx). *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

II) Relationship with sales quantity: In Prowess, firms are required to report the value and quantity of sales at the product level. Suppose the new additional capacity reported in CapEx is accurate. In that case, we expect to see a substantial correlation between the additional capacity variable (from CapEx) and sales quantity at the product level from Prowess. We expect this correlation to be tighter for the set of a new product because the sales quantity of the existing products could come from previous capacity.[76] Note we don't expect a complete correlation between sales quantity and additional capacity for several reasons. First, firms are not using the full capacity in production, and the level of capital utilization will be determined endogenously in firm optimization. Second, CapEx only reports projects that cost more than 10 million Indian rupees. Third, we only consider completed projects, not those that are stalled, abandoned, or have unreliable data. However, whether the project with unreliable data is reflected in sales quantity is unclear.

To see how additional capacity is related quantity of sales at product level we run the following regression for a new product category:

$$\text{Sales quantity}_{lt} = \beta \text{Additional Capacity}_{lt} + \epsilon_{lt} \tag{B.3}$$

[76]By new product, we mean the product that appears for the first time in the firm production line.

The result of regression is provided in Table B.3. Column 1 provides the result for the sample of all new products. The coefficient is 0.659 and strongly rejects the hypothesis that sales quantity is not related to production capacity. The R^2 of the regression is 0.491, which indicates a strong correlation of 0.70 between sales quantity and production capacity for a sample of the new product. Because the level of capital utilization is industry and product-level-specific variable, in columns 2 and 3, we provide the result of the regression by controlling for the industry and product-level fixed effect, respectively. Interestingly, the coefficient slightly increases after adding fixed effects.

	Sales quantity		
	(1)	(2)	(3)
Capacity	0.659***	0.714***	0.757***
	(0.056)	(0.069)	(0.091)
Industry FE	×	✓	×
Product FE	×	×	✓
R^2	0.491	0.569	0.737
Observations	1023	1023	1023

Table B.3: Sales quantity (from Prowess) vs. additional capacity (from CapEx) for new products

This table reports estimates of regression B.2 for the subsample of new products, where the left-hand-side variable sales quantity is from the Prowess dataset, and the right-hand-side variable is the project's additional capacity. A product would be "new" if the product was not sold by the firm in previous years. The first column does not include any fixed effects. Columns 2 and 3 include industry and firm fixed effects, respectively. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

C UIC Stylized Facts

This appendix provides more details about the across-firm variation and persistence of UIC documented in section 3.2. Furthermore, it documents for a given firm how correlated the UIC is across different product categories.

C.1 Across-Firm Variation in UIC

Table C.1 shows significant variation in $r_x^y(l,t)$. It reports summary statistics for variable $r_x^y(l,t)$. Each statistic is computed using observations across all different products and over the entire period. To calculate the statistics, we limit the sample to product-year pairs (l,t), where at least 10 firms invest in product l at time t. We do so to have enough observations for the definition of $r_x^y(l,t)$. On average, the ratio of the 75th to 25th percentile of UIC is 5.24, which is quite substantial. In other words, the dollar value of an investment for one firm might be 5.24 times higher than another firm in the same year and product category. However, both will have the same added production capacity, and the difference in the total dollar value invested comes from UIC moving from the 75th to 25th percentile of UIC. In addition, the standard deviation is large as well and shows substantial variation in this ratio across different product categories and over time. Similar results hold when we study the 90th relative to 50th percentile.

Variables	Mean	Median	StD
$r_{25}^{75}(.,.)$	5.24	2.91	2.12
$\log\left(r_{25}^{75}(.,.)\right)$	1.57	1.07	1.14
$r_{50}^{90}(.,.)$	4.25	2.75	2.14
$\log\left(r_{50}^{90}(.,.)\right)$	1.13	1.01	1.03

Table C.1: Variation in UIC

This table reports summary statistics of $r_x^y(l,t)$, which is defined as the yth percentile of UIC for product l at time t divided by the xth percentile of UIC for product l at time t. Each statistic is computed using observations across all different products and over the entire time period 1995-2003.

C.2 Firm-Level UIC Persistence Over Time

Table C.2 provides summary statistics for $\text{distance}_{within,l}$, $\text{distance}_{between,l}$, and $\text{distance}_{within,l}$-$\text{distance}_{between,l}$ defined in 3.2.2 . Note that because we only consider products with at least five projects in the sample, the number of products is smaller than the number of products in the sample.

	Mean	p25	Median	p75	StD
$\text{distance}_{within,l}$	0.79	0.11	0.56	1.06	1.11
$\text{distance}_{between,l}$	2.29	1.03	1.61	2.58	2.41
$\text{distance}_{between,l} - \text{distance}_{within,l}$	1.51	0.25	0.81	1.74	2.47
Observations	355				

Table C.2: Summary statistics for variables $\text{distance}_{within,l}$ and $\text{distance}_{between,l}$

This table reports the summary statistics for the variables $\text{distance}_{within,l}$ and $\text{distance}_{between,l}$ calculated as explained in 3.2.2. $\text{distance}_{within,l}$ measures the difference between the UIC of a firm investing in one product category multiple times over the sample. $\text{distance}_{between,l}$ measures the differences in UIC across different firms in the same product category.

C.3 Within-Firm Across-Product Variation of UIC in Multi-Product Firms

We show the correlation of UIC rank across different products offered by one firm is positive. To do so, first we categorize the UICs of given product l at time t into 10 deciles. For firm f, product l at time t, we name the corresponding decile $Rank_{lft}$[77]. Second, for firm f, product l at time t, we define a measure that captures the average rank of other products:

$$\overline{Rank}_{lft} = mean_{l' \neq l} Rank_{l'ft}$$

Now to capture how UICs of different products are correlated within a firm, we use the following regression specification:

$$Rank_{lft} = \alpha_t + \beta * \overline{Rank}_{lft} + \epsilon_{lft}$$

where α_t is the time fixed effect, and the coefficient β captures the correlation of UIC rank across different products offered by one firm. We estimate $\beta = 7.5\%$, and it is statistically significant. If every firm invests in the same UIC decile across different product categories, we expect the correlation coefficient to be 100%. On the other hand, if the decile of investment

[77]Note $Rank_{lft}$ is an integer number in interval [1,10].

in one product category is orthogonal to that in another category, we expect the beta to be 0%. Thus, even though $\beta = 7.5\%$, it is relatively small.

D Productivity Measurement

To estimate production functions, we consider all firms in Prowess that report positive revenues, capital, labor cost, and intermediate expenditures, so that a revenue production function can be estimated. We construct measures of firm-level TFP following the methodology of Ackerberg et al. (2015). They use a firm's raw-material inputs as a proxy for the unobservable productivity shocks to correct for the simultaneity in the firm's production function. The inclusion of a proxy that controls for the part of the error correlated with inputs ensures the variation in inputs related to the productivity term will be eliminated. Assuming a Cobb-Douglas production function, the estimating equation for company i in industry j at time t is

$$y_{ijt} = \alpha_j + \beta_{lj} k_{ijt} + \beta_{lj} l_{ijt} + \beta_{mj} m_{ijt} + \omega_{ijt} + \epsilon_{ijt}$$

where y denotes output, k denotes capital used, l denotes labor, and m denotes raw material expenditures. All variables are expressed in natural logarithm. The simultaneity problem arises from the ω_{ijt} term, a firm-specific, time-varying productivity shock that cannot be observed by the econometrician but may be correlated with the firm's choice of variable inputs: m, and l. Ackerberg et al. (2015) show that if the demand function for intermediate inputs is monotonic in the firm's productivity for all relevant levels of capital and labor, $m_{ijt} = m_{jt}(\omega_{ijt}, k_{ijt}, l_{ijt})$, then raw materials can serve as a valid proxy. Inverting the raw-materials demand function gives an expression for productivity as a function of capital, labor, and raw materials: $\omega_{ijt} = \omega_{jt}(m_{ijt}, k_{ijt}, l_{ijt})$. This expression can be substituted in equation above, and the coefficients on the variable inputs, l, can be estimated using semi-parametric techniques. In a second stage, the coefficients on k, l, and m are recovered using GMM techniques with the identifying assumption that productivity follows a Markov process.[78]

[78] We refer readers to Ackerberg et al. (2015) for a detailed description of the methodology.

This approach provides consistent estimates of the parameters of the production functions for each industry j. Due to the small number of companies in some of the three-digit-level industries, the production function parameters were estimated at the two-digit National Industrial Classification (NIC) codes.[79] Once we obtain the input coefficients, we construct estimates of the firm's TFP by subtracting firm i's predicted output from its actual output at time t.

E UIC and Export

In this subsection, we study the correlation between UIC and exports. We use exports as a measure of the quality of the outputs produced by the firm. Trade literature has widely documented that companies that export goods in developing countries produce, on average, higher-quality goods. Thus, we use a dummy variable for exporting to proxy for the production of high-quality output.

The first column of Table E.1 shows the estimated coefficient for regression specification 2, where the left-hand is an export dummy (the variable takes the value of one if the firm has positive export, and zero otherwise). Part II of schedule VI of The Companies Act, 1956, requires the companies to report the foreign-market activities such as the value of exported goods and the value of imported physical capital. The estimated coefficient is both economically large and statistically significant. More specifically, moving from the 25th to the 75th percentile is associated with a 2.2% higher increase in the probability of exporting. Relative to the baseline probability of exporting 57%, 2.2% is economically large. The second column indicates that consistent with the quality story, the estimated coefficient for the interaction of the scope for quality differentiation is positive and statistically significant.

[79] Due to a small number of companies, the bootstrap cannot identify separately some of the coefficients.

	Export	
ln(UIC)	0.014**	0.010**
	(0.006)	(0.005)
ln(UIC) × ln(scope$_{R\&D}$)		0.008*
		(0.004)
Controls	✓	✓
Product FE	✓	✓
Year FE	✓	✓
State FE	✓	✓
R^2	0.454	0.455
Observations	3851	3851

Table E.1: UIC and export activity

This table reports the estimates of regressions 2 for firm export activity. Export is a dummy variable taking value one iff the firm has non-zero exports. Controls include log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. Both regressions include fixed effects for product, state and year. Standard errors are double-clustered at the year and firm-level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

F Measures of Scope for Quality Differentiation

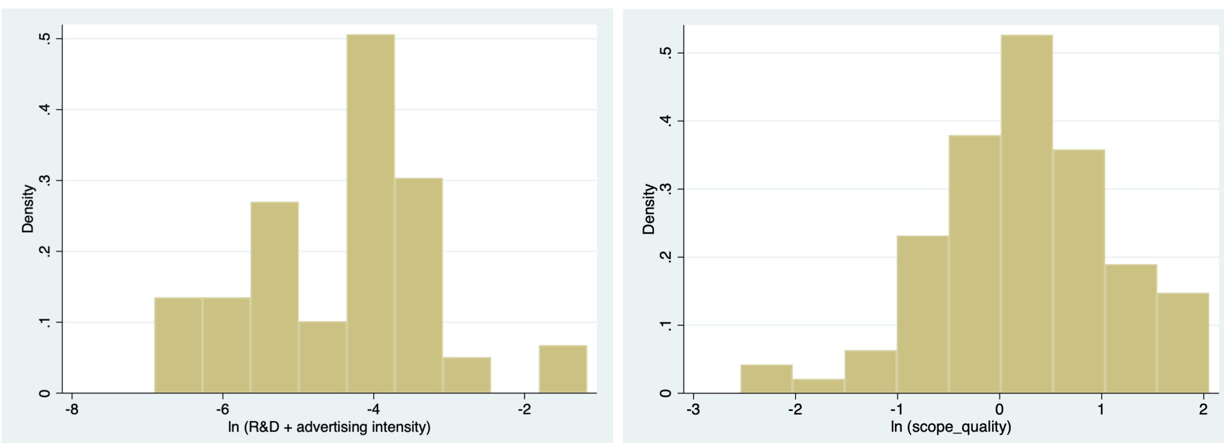
This appendix provides more details about the measures of scope for quality differentiation. We use the U.S. FTC Line of Business Program to construct $scope_{R\&D}$ following Kugler and Verhoogen (2012). The FTC Line of Business Program was in existence from 1974 to 1977. It required firms to break down advertising and R&D expenditures by industry, which makes it unique. The industry classification in the FTC Line of Business Program is similar to the 1972 Standard Industrial Classification. We hand-matched the industries in the FTC Line of Business Program to four-digit NIC using industry descriptions.[80] The summary statistics and histograms of both $scope_{R\&D}$ and $scope_{quality}$ are provided in Table F.1.

[80]For 5% of cases, the level of industries in the FTC Line of Business Program was finer, and we match these cases to a five-digit NIC code. Then, we aggregate them to the four-digit SIC industry code by taking a simple average.

	Mean	p10	Median	p90	StD
$\text{scope}_{R\&D}$	0.028	0.002	0.017	0.045	0.051
$\ln(\text{scope}_{R\&D})$	-4.415	-6.212	-4.075	-3.101	1.311
$\text{scope}_{quality}$	2.205	0.659	1.585	4.568	1.517
$\ln(\text{scope}_{quality})$	0.536	-0.416	0.461	1.519	0.748
Observations	91				

Table F.1: Summary statistics for two measures of scope for quality differentiation: $\text{scope}_{R\&D}$ and $\text{scope}_{quality}$

This table provides summary statistics for two measures of scope for quality differentiation: $\text{scope}_{R\&D}$ and $\text{scope}_{quality}$ at the the four-digit NIC level. $\text{scope}_{R\&D}$ is R&D plus advertising divided by total sales. $\text{scope}_{quality}$ is the sales-weighted standard deviation of quality (measured in subsection 3.3.2) across different products within a four-digit NIC industry.



(a) (b)

Figure F.1: Histogram of scope for two measures of scope for quality differentiation
(a) This figure plots the histogram of $\ln(\text{scope}_{R\&D})$ for four-digit NIC codes. $\text{scope}_{R\&D}$ is the sum of R&D plus advertising divided by total sales. (b) This figure plots the histogram of $\ln(\text{scope}_{quality})$ for four-digit NIC codes. $\text{scope}_{quality}$ is the sales-weighted standard deviation of quality (measured in subsection 3.3.2) across different products within a four-digit NIC industry.

G Interpretation and Magnitude of Estimated Coefficients

G.1 Firm-Level Regressions in Multi-Product Firms

	Productivity		Cost		Durability	Foreign Market
	ln(TFPR)	ln(TFPQ)	ln(Wage Bill)	ln (Material Expense)	ln(Maintenance)	Export
ln(UIC)	0.141***	0.087**	-0.094**	-0.048**	-0.029**	0.021*
	(0.050)	(0.035)	(0.041)	(0.020)	(0.016)	(0.012)
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.546	0.531	0.357	0.421	0.319	0.398
Observations	1782	1722	1782	1782	1583	1782

Table G.1: UIC and firm-outcome correlations for the subsample of single-product firms

This table reports the estimates of regressions 2 for firm-productivity, cost, durability, and export activity for the subsample of single-product firms. UIC is defined using equation 1 for each investment project. We include one observation per project for the year the project was completed. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. The wage bill includes all the different forms of compensation to employees (wages, bonuses, etc.) divided by sales. Material expense is the total payment for material inputs divided by sales. Maintenance is the repair and maintenance cost divided by PPE. Export is a dummy variable taking value one iff the firm has non-zero exports. Controls include: log(PPE) and log(total assets). Wage bill/PPE and, wage bill/sales are used as control variables for all regressions except for the wage-bill regression. All regressions include fixed effects for product category, project location's state, and year. Standard errors are double clustered at year and firm-level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

G.2 UIC of Investment vs. UIC of Capital Stock

	Productivity		Revenue			Cost		Durability	Foreign Market
	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Sales Share)	ln(Wage Bill)	ln(Material Expense)	ln(Maintenance)	Export
ln(UIC)	0.131*	0.053*	0.112***	0.151***	0.044*	-0.033*	-0.027*	-0.010	0.008
	(0.075)	(0.029)	(0.029)	(0.038)	(0.025)	(0.018)	(0.014)	(0.010)	(0.007)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.536	0.519	0.912	0.919	0.876	0.351	0.399	0.324	0.365
Observations	1424	1345	807	807	807	1424	1424	1271	1424

Table G.2: UIC and firm-outcome correlations for the subsample of new products

This table reports the estimates of regressions 2 for productivity, revenue, cost, durability, and export activity for the subsample of "new" products. A product would be "new" if the product was not available in previous years' firm products. UIC is defined using equation 1 for each investment project. UIC is defined using equation 1 for each investment project. We include one observation per project for the year the project was completed. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output quality is derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. The wage bill includes all the different forms of compensation to employees (wages, bonuses, etc.) divided by sales. Material expense is the total payment for material inputs divided by sales. Maintenance is the repair and maintenance cost divided by PPE. Export is a dummy variable taking the value of one iff the firm has non-zero exports. Controls include log(PPE) and log(total assets). Wage bill/PPE and wage bill/sales are used as control variables for all regressions except the wage-bill regression. All regressions include fixed effects for the year, project location's state, and product category. Standard errors are double clustered at year and firm-level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

H Proofs of Propositions

Using equation 8 the firm's maximization is

$$\max_{p_{out},u} \pi(p_{out}, u; A) = (p_{out} - c(u) - u)x$$

Subject to

$$xu \leq A$$

where

$$x = \zeta q^{\sigma-1} p_{out}^{-\sigma} \tag{H.1}$$

Proof of Proposition 1 The unconstrained maximization problem is equivalent to

$$\max_{p_{out},u} \pi(p_{out}, u) = (p_{out} - c(u) - u) q(u)^{\sigma-1} p_{out}^{-\sigma}$$

Using the F.O.C. wrt p_{out} we have

$$p_{out} = \frac{\sigma}{\sigma - 1}(u + c(u)) \tag{H.2}$$

Using (H.2), the maximization problem is equivalent to

$$\max_{u} \pi(u) = (\frac{q(u)}{c(u) + u})^{\sigma-1}$$

Because $\sigma > 1$ the optimum u maximizes $\frac{u^\beta}{c+c(u)}$. Because $c(u)$ is positive and $\beta < 1$, the function $\frac{u^\beta}{u+c(u)}$ reaches zero as u tends to 0 and ∞, and because it is positive, it receives the maximum at the interior point $u^*(\beta)$. Let $x^*(\beta)$ be corresponding optimum point for x. For firm to be constrained, it is necessary that $A > u^*(\beta)x^*(\beta)$. Therefore, $\bar{A}_\beta = u^*(\beta)x^*(\beta)$.

Proof of Proposition 2

Lemma: Define $d(u) = \frac{c(u)}{u}$ and $\Omega_u = \{-\frac{ud''}{d'} | u \in [0, u^*]\}$. Assume the following conditions hold:

1. Function $c(u)$ is decreasing in u.
2. $\Omega_u \subseteq [2 - \beta_{min}, 2]$, $\Omega_u \cap [2 - \beta_{min}, 2 - \beta_{min}(\frac{\sigma-1}{\sigma})] \neq \emptyset$ and $\Omega_u \cap [2 - \beta_{min}(\frac{\sigma-1}{\sigma}), 2] \neq \emptyset$.
3. Function $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d'' u}{d'}}$ is increasing in u where $\alpha = 1 + (1 - \beta)\frac{\sigma-1}{\sigma}$.

Then, in the constrained region, we have

(i) $\frac{\partial u}{\partial A} > 0$.
(ii) $\frac{\partial x}{\partial A} > 0$ iff the scope for differentiation is low.
(iii) $\frac{\partial^2 u}{\partial A \partial \beta} > 0$.
(iv) $\frac{\partial^2 x}{\partial A \partial \beta} < 0$.
(v) $\frac{\partial p_O}{\partial u} > 0$ and $\frac{\partial p_O}{\partial A} > 0$.
(vi) $\frac{\partial \text{size}}{\partial u} > 0$ and $\frac{\partial \text{size}}{\partial A} > 0$.
(vii) $\frac{\partial \text{profit}}{\partial u} > 0$ and $\frac{\partial \text{profit}}{\partial A} > 0$.
(viii) $\frac{\partial^2 p_{out}}{\partial A \partial \beta} > 0$ and $\frac{\partial^2 p_{out}}{\partial u \partial \beta} > 0$.
(ix) $\frac{\partial^2 \text{profit}}{\partial A \partial \beta} > 0$ and $\frac{\partial^2 \text{profit}}{\partial u \partial \beta} > 0$.
(x) $\frac{\partial u}{\partial \beta} > 0$ and $\frac{\partial x}{\partial \beta} < 0$.

Proof of lemma The unconstrained case has been derived in Proposition 1. We only consider constrained case here. The maximization problem would be

$$\max_{p_{out},u} \pi(p_{out}, u; , A) = (p_{out} - c(u) - u)x \tag{H.3}$$

where

$$xu = \mu A \tag{H.4}$$

Substituting (H.4) in (H.3), we reach

$$\max_{p_{out},u} \pi(p_{out}, u; , A) = \mu A \max_{p_{out},u} (\frac{p_{out} - c(u)}{u} - 1) \tag{H.5}$$

Substituting (H.4) in (H.1), we have

$$p_{out} = (\frac{\zeta}{\mu A})^{\frac{1}{\sigma}} u^{\frac{\beta(\sigma-1)+1}{\sigma}} \tag{H.6}$$

Now substituting (H.6) in (H.5), the maximization problem becomes

$$\max_u \pi(u;A) = \mu A \max_u((\frac{\zeta}{\mu A})^{\frac{1}{\sigma}} u^{-(1-\beta)(\frac{\sigma-1}{\sigma})} - \frac{c(u)}{u}) \tag{H.7}$$

Because $\lim_{u\to 0} \frac{u^\beta}{c(u)} \to 0$ and $c(u)$ is decreasing, the objective function has an interior solution.[81]

The problem is equivalent to

$$\max_u \pi(u;A) = \mu A \max_u((\frac{\zeta}{\mu A})^{\frac{1}{\sigma}} u^{-(1-\beta)(\frac{\sigma-1}{\sigma})} - d(u)) \tag{H.8}$$

Because the problem has an interior solution, FOC with respect to u leads to

$$FA^{\frac{1}{\sigma}} = \frac{-u^{-\alpha}}{d'(u)} \tag{H.9}$$

where $F = (\frac{\mu}{\zeta})^{\frac{1}{\sigma}} \frac{\sigma}{\sigma-1} \frac{1}{1-\beta}$ and $\alpha = 1 + (1-\beta)(\frac{\sigma-1}{\sigma})$. Note that because $c(u)$ is decreasing and positive, $d'(u)$ is negative.

Now taking the differential from both sides of (H.9), we have

$$\frac{\partial u}{\partial A}\frac{A}{u} = \frac{F}{\sigma} A^{\frac{1}{\sigma}} \frac{d'^2 u^\alpha}{\alpha d' + d'' u} \tag{H.10}$$

Substituting (H.9) in (H.10), we have

$$\frac{\partial u}{\partial A}\frac{A}{u} = (\frac{1}{\sigma}) \frac{1}{-\alpha - \frac{d'' u}{d'}} \tag{H.11}$$

Result 1: From (H.11), it is clear that $\frac{\partial u}{\partial A} > 0$ iff $-\frac{d'' u}{d'} > \alpha = 1 + (1-\beta)(\frac{\sigma-1}{\sigma})$.

In the constrained region, we have $xu = \mu A$, therefore, we have $\frac{\partial ln(x)}{\partial ln(A)} = 1 - \frac{\partial ln(u)}{\partial ln(A)}$. Using (H.11), we have

[81] It is easy to show the objective function tends toward $-\infty$ as $u \to 0$ and tends toward zero as $u \to \infty$.

$$\frac{\partial ln(x)}{\partial ln(A)} = 1 - (\frac{1}{\sigma})\frac{1}{-\alpha - \frac{d''u}{d'}} \tag{H.12}$$

Result 2: From (H.12), it is clear that $\frac{\partial x}{\partial A} > 0$ iff $-\frac{d''u}{d'} > 2 - \beta(\frac{\sigma-1}{\sigma})$.

Using (H.6), we have $\frac{\partial ln(p_{out})}{\partial ln(A)} = -\frac{1}{\sigma} + \frac{\beta(\sigma-1)+1}{\sigma}\frac{\partial ln(u)}{\partial ln(A)}$. Now using (H.11) we have

$$\frac{\partial ln(p_{out})}{\partial ln(A)} = -\frac{1}{\sigma} + \frac{\beta(\sigma-1)+1}{\sigma^2}\frac{1}{-\alpha - \frac{d''u}{d'}} \tag{H.13}$$

Result 3: Rearranging (H.13) we have $\frac{\partial p_{out}}{\partial A} > 0$ iff $-\frac{d''u}{d'} < 2$.

Let's define $size = p_{out}.x$. Therefore, we have $\frac{\partial ln(size)}{\partial ln(A)} = \frac{\partial ln(x)}{\partial ln(A)} + \frac{\partial ln(p_{out})}{\partial ln(A)}$. Using (H.12) and (H.13), we have

$$\frac{\partial ln(size)}{\partial ln(A)} = \frac{\sigma-1}{\sigma} - \frac{(1-\beta)(\sigma-1)}{\sigma^2}\frac{1}{-\alpha - \frac{d''u}{d'}} \tag{H.14}$$

Result 4: Rearranging (H.14), we have $\frac{\partial size}{\partial A} > 0$ iff $-\frac{d''u}{d'} > 2 - \beta$.

Using (H.9), we can write

$$GA^{\frac{1}{\sigma}} = \frac{-u^{-\alpha}}{d'(u)}(1-\beta) \tag{H.15}$$

Where $G = (\frac{\mu}{\zeta})^{\frac{1}{\sigma}}\frac{\sigma}{\sigma-1}$ is not a function of A and β. We have $\alpha = 1 + (1-\beta)(\frac{\sigma-1}{\sigma})$. Taking the logarithm from both side

$$ln(GA^{\frac{1}{\sigma}}) = -\alpha ln(u) + ln(\frac{-1}{d'(u)}) + ln(1-\beta) \tag{H.16}$$

Consider that α and u are function of β. Taking the derivative respect to beta from both sides and rearranging, we have

$$\frac{\partial u}{\partial \beta} = \frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}} \tag{H.17}$$

If $-\frac{d''u}{d'} > \alpha$ then from Result 1, we have $\frac{\partial u}{\partial A} > 0$.Therefore, to have $\frac{\partial^2 u}{\partial A \partial \beta} > 0$, we just need $\frac{\partial u}{\partial \beta}$ to be increasing in u.

Result 5: If $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}}$ is increasing in u iff $\frac{\partial^2 u}{\partial A \partial \beta} > 0$.

Because $ux = \mu A$, $\frac{\partial^2 ln(u)}{\partial A \partial \beta} + \frac{\partial^2 ln(x)}{\partial A \partial \beta} = 0$.
Result 6: If $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}}$ is increasing in u iff $\frac{\partial^2 x}{\partial A \partial \beta} < 0$.

Using (H.6), we have $ln(p_{out}) = -\frac{1}{\sigma} ln(A) + \frac{\beta(\sigma-1)+1}{\sigma} ln(u)$. Taking derivative respect to $ln(A)$ we have $\frac{\partial ln(p_{out})}{\partial ln(A)} = -\frac{1}{\sigma} + \frac{\beta(\sigma-1)+1}{\sigma} \frac{\partial ln(u)}{\partial ln(A)}$. Taking the derivative respect to β from both sides

$$\frac{\partial^2 ln(p_{out})}{\partial A \partial \beta} = \frac{\sigma - 1}{\sigma} \frac{\partial ln(u)}{\partial ln(A)} + \frac{\beta(\sigma-1)+1}{\sigma} \frac{\partial^2 ln(u)}{\partial A \partial \beta} \tag{H.18}$$

Result 7: If $\frac{\partial ln(u)}{\partial ln(A)} > 0$ and $\frac{\partial^2 u}{\partial A \partial \beta} > 0$ then $\frac{\partial^2 p_{out}}{\partial A \partial \beta} > 0$.

Using (H.17), we only need $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}}$ be increasing in u. Because $xu = \mu A$, if u is increasing in β, x would be decreasing in β.

Result 8: $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}}$ is increasing in u iff $\frac{\partial u}{\partial \beta} > 0$ and $\frac{\partial x}{\partial \beta} < 0$.

Back to (H.7), the firm profit maximization in the constrained region is equivalent to

$$\max_u \pi(u; A, \beta) = \mu A \max_u ((\frac{\zeta}{\mu A})^{\frac{1}{\sigma}} u^{-(1-\beta)(\frac{\sigma-1}{\sigma})} - \frac{c(u)}{u} - 1) \tag{H.19}$$

Using the envelope theorem with respect to β, we have

$$\frac{\partial \pi}{\partial \beta} = \mu A^{1-\frac{1}{\sigma}} (\frac{\zeta}{\mu})^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} ln(u) u^{-(1-\beta)(\frac{\sigma-1}{\sigma})} \tag{H.20}$$

If we can show function $ln(u)A^{1-\frac{1}{\sigma}}u^{-(1-\beta)(\frac{\sigma-1}{\sigma})}$ is increasing in A then from (H.20), it is clear that $\frac{\partial^2 profit}{\partial A \partial \beta} > 0$. To show that it is sufficient to prove $A^{1-\frac{1}{\sigma}}u^{-(1-\beta)(\frac{\sigma-1}{\sigma})}$ (or $Au^{-(1-\beta)}$) is increasing in A. Let $G = Au^{-(1-\beta)}$. Then

$$\frac{\partial ln(G)}{\partial ln(A)} = 1 - \frac{\partial ln(u)}{\partial ln(A)}(1-\beta)$$

Using (H.11), we have

$$\frac{\partial ln(G)}{\partial ln(A)} = 1 - (\frac{1}{\sigma})\frac{1}{-\alpha - \frac{d''u}{d'}}(1-\beta) \tag{H.21}$$

Rearranging (H.21) yields to $\frac{\partial ln(G)}{\partial ln(A)} > 0$ iff $-\frac{d''u}{d'} > 2 - \beta$.
Result 9: If $-\frac{d''u}{d'} > 2-\beta$ then $\frac{\partial^2 profit}{\partial A \partial \beta} > 0$.

Result 1 through **Result 9** proves the **lemma**.

It is enough to show that under the conditions mentioned in proposition 2, the conditions in the lemma hold. Going back to the proof of Proposition 1, the maximization problem for the unconstrained case is equivalent to

$$\max_u (\frac{u^\beta}{c(u)+u})$$

If $u^* > (\frac{a}{b})^{1/k}$ because $\beta < 1$ then by moving u^* closer to $(\frac{a}{b})^{1/k}$, the objective function increases; therefore, $u^* \leq (\frac{a}{b})^{1/k}$.

Going back to the proof of lemma for the constrained case, the optimization problem is equivalent to

$$\max_u \pi(u;A) = \mu A \max_u ((\frac{\zeta}{\mu A})^{\frac{1}{\sigma}} u^{-(1-\beta)(\frac{\sigma-1}{\sigma})} - \frac{c(u)}{u}) \tag{H.22}$$

If $u(A) > (\frac{a}{b})^{1/k}$ because $-(1-\beta)(\frac{\sigma-1}{\sigma}) < 0$ then by moving $u(A)$ closer to $\frac{a}{b})^{1/k}$, the objective function increases; therefore, $u(A) \leq (\frac{a}{b})^{1/k}$. Therefore, we only focus on interval $\big(0, (\frac{a}{b})^{1/k}\big)$.

For function $c(u)$ mentioned in proposition 2, $d(u) = \frac{a-bu^k}{u}$. It is easy to show that

$$\frac{-d''u}{d'} = 2 - \frac{k}{1 + \frac{au^{-k}}{b(k-1)}} \tag{H.23}$$

The first condition in the lemma holds obviously. To check condition 2, we need $2 - \frac{k}{1+\frac{au^{-k}}{b(k-1)}} \in [2-\beta_{min}, 2]$, which is equivalent to $\frac{k}{1+\frac{au^{-k}}{b(k-1)}} \in [0, \beta_{min}]$. Because $K > 1$, we have $\frac{k}{1+\frac{au^{-k}}{b(k-1)}} > 0$. It is enough to show that $\frac{k}{1+\frac{au^{-k}}{b(k-1)}} < \beta_{min}$. The function $\frac{k}{1+\frac{au^{-k}}{b(k-1)}}$ is increasing in u reaches it's maximum at $u = (\frac{a}{b})^{(1/k)}$. We just need to have $1 < k < 1 + \beta_{min}$. Therefore, condition 2 holds.

To check condition 3, we need $\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha - \frac{d''u}{d'}}$ to be increasing in u. Using (H.9), we need to show that

$$\frac{u((\frac{1}{1-\beta}) - \frac{\sigma-1}{\sigma} ln(u))}{-\alpha + 2 - \frac{k}{1+\frac{au^{-k}}{b(k-1)}}} \tag{H.24}$$

is increasing in u. Consider that the denominator is positive because $-\frac{d''u}{d'} > 2 - \beta_{min}(\frac{\sigma-1}{\sigma}) > \alpha$, which means $-\frac{d''u}{d'} - \alpha > 0$. Also notice the denominator is decreasing in u. Therefore, it is enough to show nominator is increasing in u. To show the nominator is increasing in u, we need the derivative of the nominator to be positive, which is equivalent to $\frac{1}{1-\beta} > \frac{\sigma-1}{\sigma}(1 + ln(u))$. Because $u < (\frac{a}{b})^{1/k}$, we just need to have $\frac{1}{1-\beta} > \frac{\sigma-1}{\sigma}(1 + \frac{1}{k} ln(a/b))$. Now, to have it for all β, it is enough to have $\frac{1}{1-\beta_{min}} > \frac{\sigma-1}{\sigma}(1 + \frac{1}{k} ln(a/b))$.

I Debt Recovery Tribunals

I.1 Debt Recovery Tribunals Establishment Dates

Table I.1 lists the establishment date for each DRT and its jurisdiction under the Recovery of Debt Due to Banks and Financial Institutions Act, 1993.

Date of Establishment	States	Financial Year
Apr 27 1994	Andaman & Nicobar Islands, West Bengal	1995
Jul 5 1994	Delhi	1995
Aug 30 1994	Chandigarh, Haryana, Himachal Pradesh	1995
	Punjab, Rajasthan	
Nov 30 1994	Karnataka, Andhra Pradesh	1995
Dec 21 1994	Daman & Diu, Dadra & Nagar Haveli, Gujarat	1995
Nov 4 1996	Kerala, Pondicherry, Tamil Nadu	1997
Jan 7 1997	Arunachal Pradesh, Assam, Manipur, Meghalaya	1997
	Mizoram, Nagaland, Tripura	
Jan 24 1997	Bihar, Orissa	1997
Apr 7 1998	Madhya Pradesh, Uttar Pradesh	1999
Jul 16 1999	Goa, Maharashtra	2000

Table I.1: Dates of DRT establishment across different states in India

This table provides the establishment date for each DRT and its jurisdiction under the Recovery of Debt Due to Banks and Financial Institutions Act, 1993.

I.2 Pre-trend Analysis

We conduct a pre-trend analysis in Table I.2. In practice, in regression 9 and 10, we replace the DRT dummy with three dummy variables: Before^{-1} is a dummy variable that equals one if the firm is incorporated in a state that will pass DRT in one year. Before^{0} is a dummy variable that equals one if the firm is incorporated in a state that passes DRT this year. After^{+1} is a dummy variable that equals one if the firm is incorporated in a state that passed DRT at least one or more years ago. More precisely, we use following regression specification when the output variable of interest is at the firm level:

$$y_{kft} = \alpha_f + \alpha_t + \alpha_k + \lambda X_{ft} + \beta_{-1}\text{Before}^{-1} + \beta_0\text{Before}^0 + \beta_{+1}\text{After}^{+1} + \varepsilon_{kft} \tag{I.1}$$

We use the following regression specification when the output variable of interest is at the product level:

$$y_{kft} = \alpha_l + \alpha_t + \alpha_k + \lambda X_{ft} + \beta_{-1}\text{Before}^{-1} + \beta_0\text{Before}^0 + \beta_{+1}\text{After}^{+1} + \varepsilon_{kft} \tag{I.2}$$

The dummy variable Before^{-1} allows us to assess whether any output effect can be found prior to the introduction of DRT. Finding such an effect of the legislation prior to its introduction could be symptomatic of some reverse causation and inconsistent with the parallel-trend-assumption. In fact, the estimated coefficient on Before^{-1} is economically and statistically insignificant.

	ln(Total Debt)	ln(CAPEX)	ln(TFPR)	ln(TFPQ)	ln(Project Cost)	ln(UIC)	ln(output price)	ln(output quality)
$Before^{-1}$	0.003	0.009	0.008	0.005	0.021	-0.028	0.005	0.006
	(0.010)	(0.024)	(0.026)	(0.021)	(0.051)	(0.074)	0.017	0.023
$Before^{0}$	0.043**	0.037**	0.036**	0.019*	0.101**	0.107***	0.029***	0.023*
	(0.018)	(0.014)	(0.015)	(0.011)	(0.045)	(0.024)	(0.008)	(0.012)
$After^{+1}$	0.067***	0.049***	0.044***	0.031**	0.081**	0.091**	0.016*	0.031***
	(0.021)	(0.015)	(0.014)	(0.013)	(0.034)	(0.038)	(0.009)	(0.011)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	×	×	×	×
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Product FE	×	×	×	×	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.816	0.801	0.558	0.539	0.671	0.830	0.895	0.901
Observations	2722	2722	2722	2619	3851	3851	1953	1953

Table I.2: Pre-trend Analysis of DRT effect

This table reports the estimates of regression I.1 and I.2 to study pre-trend for the effects of DRT on debt, investment, TFP, project cost, UIC, output price, and quality. Before^{-1} is a dummy variable that equals one if the firm is incorporated in a state that will pass DRT in one year. Before^{0} is a dummy variable that equals one if the firm is incorporated in a state that passes DRT this year. After^{+1} is a dummy variable that equals one if the firm is incorporated in a state that passed DRT at least one or more years ago. Total debt consists of both-short and long-term debt. CAPEX = Δ PPE + Depreciation, and TFP is a measure productivity using the ACF method. Columns 4 and 5 present the estimates for project cost and UIC (project cost = UIC$\times$ additional capacity). Output "quality" is derived from equation 3 with $\sigma = 5$. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the year, firm's headquarter state. The first four columns have firm fixed effects, and the next four columns have product fixed effects. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

I.3 Effect of DRT on Other Investment Measures

Column 1 in I.3 shows the introduction of DRTs increases firm balance-sheet CAPEX (conditional on investing) by 5% for a sample of all firms in Prowess during the sample period, consistent with the idea that aggregate credit increased as a result of the improved enforcement. In columns 2 and 3 we decompose this impact by dividing the firm-year sample into a sub-samples with at least one CapEx project and a sub-sample without CapEx projects.[82]

[82] If a firm in a specific year has at least one CapEx project, we put that firm in the first sub sample only for that particular year.

Columns 2 and 3 indicates nearly 80% of the impact comes from the sub-sample with at least one CapEx project.

In columns 4-6, we estimate the model only for sub-sample of firms with at least one project in CapEx. In Column 4, we find the introduction of DRTs increased the balance-sheet CAPEX by 4% for the subsample of firms with projects in CapEx. The point estimate is slghtly smaller than what we found for the whole sample of Prowess. To see the impact of DRTs establishment on the project cost at firm level, we add all project costs in which the firm is involved. In column 5, our dependent variable is "Sum Project Cost" and we find the sum project cost at firm level increased by 4.8% by DRTs establishment. To examine the effect of DRTs introduction on the project level at the product level, we run a regression 9. The last column in I.3 shows the introduction of DRTs increased the project cost (conditional on investing) by 9.2%.

	All Firms			Firms with Project		
	ln(CAPEX)	ln(CAPEX)$\times 1_{CapEx}$	ln(CAPEX)$\times 1'_{CapEx}$	ln(CAPEX)	ln(Sum Project Costs)	ln(Project Cost)
DRT	0.049**	0.040***	0.010	0.041***	0.048**	0.092**
	(0.021)	(0.011)	(0.023)	(0.013)	(0.021)	(0.041)
Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	×
Product FE	×	×	×	×	×	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.873	0.875	0.853	0.874	0.812	0.693
Observations	21436	21436	21436	2675	2722	3851

Table I.3: DRT and Different Measures of Investment

This table presents estimates of regressions 9 and 10 for different measures of investment. We use model specification 9 for columns 1-5 and model 10 for the last column. In the first three columns, CAPEX is balance-sheet CAPEX (=Δ PPE + Depreciation). The first three columns include all observations in the Prowess dataset. 1_{CapEx} is a dummy variable that takes the value of one iff the firm had at least one project in CapEx that was completed that year. $1'_{CapEx}$ = 1 - 1_{CapEx}. In column 4, we focus on the sub-sample of firm-year with at least one project in the CapEx dataset. In column 5, the variable "Sum Project Costs" is the sum of all firm's project cost in that year. In column 6, we use project cost at the product level. Controls include log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the year, firm's headquarter state. All regressions except the last column include firm fixed effects. The last column controls for product category fixed effect. Standard errors (in parentheses) are clustered at the state level.*, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels.

I.4 Using DRT as an Instrument Variable for UIC

In this subsection, we use the establishment of DRTs as an IV for UIC to provide reduced-form estimates of the effect of UIC on firm outcomes. This exercise relies on the assumption that the exclusion restriction holds; that is, the establishment of DRTs affects firm-level outcomes only through changes in UIC. The evidence provided so far seems to suggest this assumption is likely to hold. However, estimates from this regression need to be taken with a grain of salt. This exercise aims to provide an estimate for the effect of UIC on firm-level outcomes, assuming the exclusion restriction holds. We run the following two-stage least squares (2SLS) regression specification and use the establishment of DRTs as the IV:

$$y_{lkft} = \alpha_l + \alpha_t + \alpha_k + \beta \times ln(\text{UIC}_{lkft}) + \lambda X_{ft} + \varepsilon_{lkft} \tag{I.3}$$

Except for the right-hand side variable $ln(\text{UIC}_{lkft})$, this regression is the same as regression specification 10.

Table I.4 reports the estimated coefficients. The higher UIC increases firm performance, price, quality, sales share, and the likelihood of export. More specifically, we estimate that a 10% increase in UIC increases TFP, ROE, Tobin's Q, output price, output quality, sales share, and the likelihood of export by 1.4%, 0.9%, 1.4%, 1.5%, 1.9%, 0.5%, and 0.2%, respectively. The estimated coefficients are economically and statistically significant.

	Productivity		Revenue			Foreign Market
	ln(TFPR)	ln(TFPQ)	ln(price)	ln(quality)	ln(sales share)	Export
ln(UIC)	0.145***	0.078**	0.109**	0.193***	0.053**	0.015*
	(0.046)	(0.032)	(0.043)	(0.059)	(0.024)	(0.008)
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Observations	3851	3701	1953	1953	1953	3851

Table I.4: Effect of DRT on firm performance using DRT as an IV for UIC

This table reports the 2SLS estimates of the effect of UIC on firm performance, revenue, and TFP components, and export likelihood using DRT as an instrument variable, using regression specification I.3. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output "quality" is derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. Export is a dummy variable that takes the value of one iff the firm has non-zero export. All regressions include firm-level controls and fixed effects for the product, project location's state, and year. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

J Interaction with $scope_{quality}$

This appendix repeats the regressions used for Tables 3 and 6. The only difference is that that we use $scope_{quality}$ (defined in subsection 3.3.5) instead of $scope_{R\&D}$ as a measure of scope for quality differentiation.

	Productivity		Revenue			Foreign Market
	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Sales Share)	Export
ln(UIC)	0.112**	0.053*	0.087***	0.116***	0.034*	0.010**
	(0.045)	(0.029)	(0.025)	(0.028)	(0.019)	(0.005)
ln(UIC) $\times ln(scope_{quality})$	0.112**	0.061*	0.067**	0.089**	0.026*	0.007
	(0.050)	(0.033)	(0.032)	(0.034)	(0.014)	(0.004)
Controls	✓	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
R^2	0.627	0.594	0.966	0.959	0.916	0.457
Observations	3851	3701	1953	1953	1953	3851

Table J.1: Heterogeneity in UIC and firm outcome correlations: interaction with scope for quality differentiation, $scope_{quality}$

This table presents estimates of regression 2 for TFPR, TFPQ, revenue components, and export dummy where an interaction term between $ln(UIC)$ and $scope_{quality}$ is added to the right-hand-side variables. UIC is defined using equation 1 for each investment project. We include one observation per project for the year the project was completed. scope$_{quality}$ is defined in equation 4 and is the sales-weighted standard deviation of quality (measured in subsection 3.3.2) across different products within a four-digit NIC industry. ln(scope$_{quality}$) has been deviated from the ample median. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. Output quality derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. Export is a dummy variable taking the value of one iff the firm has non-zero exports. Controls include log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for product category, year, and project location's state. Standard errors are double clustered at year and firm level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level.

	Project-Cost Decomposition			Productivity		Revenue			
	ln(UIC)	ln(Capacity)	ln(Project Cost)	ln(TFPR)	ln(TFPQ)	ln(Price)	ln(Quality)	ln(Quantity)	ln(Sales)
DRT	0.069***	0.013	0.082**	0.031**	0.024*	0.018***	0.026**	0.027*	0.045*
	(0.023)	(0.046)	(0.039)	(0.014)	(0.013)	(0.006)	(0.010)	(0.014)	(0.024)
DRT× ln(scope$_{quality}$)	0.093*	-0.032*	0.061	0.039**	-0.002	0.027**	0.038***	-0.009	0.014*
	(0.049)	(0.017)	(0.079)	(0.015)	(0.012)	(0.011)	(0.012)	(0.019)	(0.008)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	×	×	×	✓	✓	×	×	×	×
Product FE	✓	✓	✓	×	×	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.835	0.833	0.706	0.559	0.539	0.915	0.879	0.937	0.926
Observations	3851	3851	3851	2722	2619	1953	1953	1953	1953

Table J.2: Heterogeneous effect of DRT: interaction with scope for quality differentiation, $scope_{quality}$

This table reports the estimates of the heterogeneous effect of DRT on project-cost components, revenue, and productivity using regressions 11 and 12. scope$_{quality}$ is defined in equation 4 and is the sales-weighted standard deviation of quality (measured in subsection 3.3.2) across different products within a four-digit NIC industry. ln(scope$_{quality}$) has been deviated from sample median. Columns 1-3 presents the estimates for the project cost, UIC, and additional capacity added to the firm by the project (project cost = UIC × additional capacity). Columns 4-7 are the estimated coefficients for revenue and revenue components of TFP. Output quality is derived from equation 3 with $\sigma = 5$. Sales share is the share of products sold in a product category. TFPR is estimated using the ACF estimation method. TFPQ is estimated by dividing TFPR by a sales-weighted average price of output. All regressions include firm-level controls and fixed effects for year and firm's headquarter state. Regressions for firm-performance measures and cost components of TFP include firm fixed effects. The regressions for the revenue component of TFP include product fixed effects. Standard errors (in parentheses) are clustered at the state level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.

K Import of physical Capital

We use the value of imported physical capital to study whether UIC is correlated with the import of physical capital. We use the regression specification 2. The left-hand-side variable is either a dummy variable for physical-capital import (takes a value of one if the value of imported physical-capital is non-zero, and is zero otherwise) or the share of imported physical capital (value of physical capital imported divided by PPE) to test the hypothesis.[83]

[83] In India, Part II of schedule VI of The Companies Act, 1956, requires firms to report the value of imported physical capital.

The result is provided in Table K.1. The first column reports the regression results for a dummy variable equal to one if the value of imported physical capital is non-zero for the firm in that year. The estimates suggest a statistically significant association between UIC and the likelihood of physical capital import. More specifically, moving from the 25th to the 75th percentile of UIC is associated with a 2.1% higher likelihood of physical-capital import. In the second column, we limit the sample to a sub-sample of firms with positive physical-capital imports. We define the share of physical capital imported as the ratio of a firm's imported physical capital to the value of the firm's stock of capital, measured by PPE. The point estimate suggests that a 10% increase in UIC is associated with a 0.3% higher share of physical-capital import. In particular, moving from the 25th to 75th percentile of UIC is associated with a 4.5% higher share of imported physical capital.

	Import of Physical-Capital	ln(Share of Physical-Capital Imported)
ln(UIC)	0.013**	0.029**
	(0.005)	(0.014)
Controls	✓	✓
Product FE	✓	✓
Year FE	✓	✓
State FE	✓	✓
R^2	0.431	0.671
Observations	3851	2231

Table K.1: UIC and physical-capital import

This table reports estimates of regression 2 for the firm's imported physical-capital. Import of Physical Capital is a dummy variable that takes the value of one iff the firm has positive imported physical-capital. Share of physical-Capital Imported is the firm's imported physical-capital divided by the firm's total stock of physical-capital (measured by PPE). All regressions include firm-level controls and fixed effects for the year, project location's state, and product category. Standard errors (in parentheses) are double-clustered at the firm and year level. *, **, and *** indicate significance at the 0.1, 0.05 and 0.01 level, respectively.

L Stock Market Response

In this section, we study the stock market's response to the announcement of the project cost and additional capacity of the investment projects using the daily return around the project announcement date. Studying the stock market response serves several purposes. First, the estimated coefficients in Table 2 are not causal. Second, the estimated coefficients in Table 2 are likely to be an underestimate for the "full" effect of higher-UIC capital on firms for a few reasons: (1) We use project-level investment data, and new projects are only a fraction of the firm's total stock of physical capital.[84] Thus, when studying a firm-level outcome, such as TFP, we study the effect of new physical capital and the existing stock of physical capital together. (2) We only study annual firm-level outcomes for the year that the project was completed. Since firms use physical capital for several years, the estimated coefficient does not capture the total effect of using higher-UIC capital over the life of the physical capital. (3) Once a project is completed, firms might not fully utilize the newly created capacity to produce output.

We focus on a sub-sample of project-level data for this subsection. First, we limit the sample to publicly traded firms for which we have the stock prices. Second, we restrict the sample to projects with information about the capacity and project cost at the announcement date (for some projects, the capacity and project cost are announced at a later date). Third, we drop projects for which the UIC changes after the announcement date. We do because as explained earlier, we use the UIC of the last announcement as the project UIC in all our regressions. If we included these observations in our regression, we would contaminate our estimates with the market's expectation about a later change in project details.

To measure the stock market's reaction, we calculate the three-day cumulative abnormal return (adjusted by one-factor Capital Asset Pricing Model (CAPM)) around the project announcement date using the standard event-study methodology. Abnormal returns are estimated as the difference between the return on a firm's stock and the return predicted by CAPM, where beta is estimated using the daily correlation of the return on the firm's stock and an Indian stock market index S&P Nifty, as the benchmark market portfolio. The estimation window used for calculating beta has a length of 150 days and ends three weeks before the announcement date (-170 to -21 days before the announcement date).

Table L.1 shows the results of regression 2 for abnormal stock market return. Column 1 shows the announcement of projects with higher-UIC capital is associated with higher abnormal returns around the announcement date. Moving from the 25th percentile to the 75th percentile of UIC is associated with a 0.63% higher abnormal return. In column 2,

[84] On average, the cost of an investment project is a third of the firm's total PPE.

we study the interaction of UIC with the scope for quality differentiation. We find the abnormal returns are stronger for industries with more scope for quality differentiation. This finding is consistent with the findings in the prior section, where we show UIC has a higher correlation with TFP in industries with higher scope for quality differentiation.[85] In particular, moving from the 25th percentile to the 75th percentile of UIC is associated with a 2.81% higher abnormal return in an industry with one standard deviation more scope for quality differentiation relative to the median.

Columns 3 and 4 of Table L.1 are similar to columns 1 and 2. The only difference is that we control for the project's additional capacity. We do so because differences in additional capacity could be driving the results. However, after controlling for additional capacity, the estimated coefficient becomes slightly larger. Column 3 estimate suggests that moving from the 25th percentile to the 75th percentile of UIC is associated with a 0.85% higher abnormal return. Column 4 estimate suggests moving from the 25th percentile to the 75th percentile of UIC is associated with a 2.62% higher abnormal return in an industry with one-standard-deviation-higher scope relative to the median.

We do a back-of-the-envelope calculation to estimate the effect of UIC on the investment project's Net Present Value (NPV). The average firm market cap during the sample is 415 million USD. Thus, the value added to the firm moving from the 25th to the 75th percentile of UIC is, on average, $0.85\% \times 415$ million USD$=$ 3.5 million USD. Because an average project costs about 78 million USD, moving from the 25th to the 75th percentile of UIC has an NPV equal to $3.5/78 = 4.5\%$ of the average project cost. These numbers should be taken with a grain of salt for two reasons. First, the calculated NPV is relative to the stock market participant's expectations before the project's announcement. Thus, if stock market participants already expect a high probability of firm announcing a particular project, this number could be an underestimate. Second, other unobservable differences correlated with UIC could be driving the abnormal return, as well.

[85] The results are robust when we add Tobin's Q, which is common in firm-level return regressions.

	Abnormal Return			
ln(UIC)	0.004**	0.003	0.005**	0.005*
	(0.002)	(0.002)	(0.002)	(0.003)
ln(UIC) $\times$ ln(scope$_{R\&D}$)		0.011**		0.009*
		(0.005)		(0.005)
ln(Add Capacity)			0.003	0.004
			(0.003)	(0.004)
ln(Add Capacity) $\times$ ln(scope$_{R\&D}$)				-0.011
				(0.016)
Controls	✓	✓	✓	✓
Product FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
R^2	0.218	0.219	0.219	0.220
Observations	1375	1375	1375	1375

Table L.1: UIC and stock market reaction to project announcement

This table presents estimates of regression 2 for abnormal stock market return (adjusted by one-factor Capital Asset Pricing Model (CAPM) using S&P Nifty as the stock market index) over a 3-day window around the project's announcement dates. We limit the sample to publicly traded firms for which we have the stock prices and the sample of projects with information about the capacity and project cost at the announcement date. We also drop projects for which the project cost or capacity changes after the announcement date. UIC is defined using equation 1 for each investment project. Add Capacity is additional capacity added to the firm by the project(project cost = UIC$\times$additional capacity). scope$_{R\&D}$ is advertising plus R&D divided by total industry sales for four-digit NIC industry codes. ln(scope$_{R\&D}$) has been deviated from the sample median. Controls include: log(PPE), log(total assets), wage bill/PPE, and wage bill/sales. All regressions include fixed effects for the product, project location's state, and year. Standard errors (in parentheses) are double clustered at the firm and year level. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 level, respectively.