Firm Heterogeneity, Demand for Quality and Prices: Evidence from India

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Abstract

Markups vary systematically across firms and are an important cause of productivity dispersion. However, whether markup dispersion represents misallocation depends on sources driving the dispersion. This paper provides evidence on the role of demand-side factors in shaping the dispersion of markups. Using data on Indian manufacturing firms, I first document two key correlations: prices and markups are increasing in firm size. I then explore how these correlations are driven by two factors: the *assortative matching* of wealthier consumers to larger firms, and the lower demand elasticity of wealthier consumers. Guided by this observation, I examine how firms adjust prices to income shocks to poor households. Using weather-driven exogenous changes to local rural income, I find that average prices *decrease* when demand from poor households increases relative to wealthier households. These effects are due to changes in markups rather than production costs, and are driven by firms that sell to both rich and poor households. The results are supportive of the demand-based markup channel: selling to wealthier and less demand elastic households leads larger firms to charge higher markups. The channel accounts for at least 8 percent of the observed productivity dispersion across the Indian manufacturing sector. This suggests that the welfare gains from resource reallocation are likely to be lower than otherwise implied by standard models.

Keywords: Misallocation, Markups, Demand shocks, Income Inequality

JEL Classification: D24, D31, L11, O11, O47

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I Introduction

It is well documented that firms differ in productivity, even within narrowly defined industries. Moreover, this heterogeneity is more prominent across low- and middle-income countries and suggests the existence of frictions that prevent efficient allocation of resources in an industry, or an economy at large (Restuccia and Rogerson (2008); Hsieh and Klenow (2009)). A number of recent studies argue that an important underlying cause of these large productivity differences is variation in markups. The natural question then, particularly from a policy standpoint, is to understand what drives markup dispersion. If the observed variation in markups stems largely from inefficient sources, such as product market distortions, then policies that reallocate resources can increase aggregate productivity. However, if driven by efficient sources, such as differences in consumer demand elasticities faced by firms, potential gains from reallocating resources across firms will be limited. A large literature has taken markup dispersion as evidence of allocative inefficiencies as given, with little consideration on how this dispersion is influenced by demand factors.

This paper investigates the role of demand-side features in shaping the dispersion of markups within industries. Specifically, I show that segmentation in product market coupled with differences in demand elasticities across consumers with different income levels can allow large systematic dispersion in markups to persist in equilibrium. As a result, dispersion in revenue total factor productivity (TFPR) arises naturally in presence of consumer demand heterogeneity. A direct implication is that gains from reallocating resources across firms would be limited because larger firms charge higher markups as they face low demand elasticities and not due to underlying market inefficiencies.

I develop my argument in two steps. In the first part of the paper, I use detailed micro data from Indian Annual Survey of Industries on manufacturing firms' input usage and final output to estimate firm-product level markups and marginal cost, by building on the work of De Loecker et al. (2016). I document a systematic relation between firm size and the prices, marginal costs and markups for its products. First, prices (within a product group) are increasing in firm size.[1] Second, marginal cost is increasing in firm size. This finding is consistent with the literature on product quality (Verhoogen (2008); Kugler and Verhoogen (2011)), and in line with the findings in these papers, I find that input material prices, wages and capital intensity are higher for larger firms. Third, and most important, markups are also increasing in firm size. These patterns are more pronounced in sectors with greater scope for quality differentiation, as proxied by the Rauch (1999) classification of non-homogeneous goods.

At the heart of the economic mechanism driving these correlations is *assortative matching* — that is, the tendency of wealthier consumers to source their consumption from goods produced by larger firms. The approach is motivated by two theoretical ideas. First, following Linder (1961), consumers are asymmetric in income and their willingness to pay for product quality; and firms producing higher quality varieties cater to the demand of wealthier households. Second, firm productivity and input quality are complements in determining output quality, as in Kugler and Verhoogen (2011), and in equilibrium

[1] A product group is the most refined category to which a product belongs in the data. Few examples of product category include cotton shirts, wooden chair, black tea, sugar, cotton yarn. While unit of measurement could vary across groups, all products within the same group are measured in the same units.

higher quality is produced by more productive and larger firms. Taken together, this implies that wealthier households source larger share of their consumption from goods produced by larger firms. This matching on product quality has two implications. First, as wealthier households are less price sensitive, selling to wealthier households leads larger firms to charge higher markups. Second, an increase in the demand from the poorer income group makes the marginal consumer more demand elastic for firms that sell to both rich and poor households, proxied in my data by firms in the middle of the size distribution. These firms respond by lowering their markups and prices. I term this as the *demand composition* channel.

The second part of the paper provides evidence on the demand composition channel using weather-driven source of exogenous variation in consumer demand. Specifically, to test the causal claim that increases in demand from the poor lead to higher demand elasticity for firms and a fall in markups and prices, I propose an empirical strategy that uses quasi-random income shocks to poor households as a source of fluctuation in their demand. Like many developing countries, the majority of the poor in India are employed in agricultural sector and face substantial productivity risk — even today, less than one-third of the agricultural land is irrigated, making agricultural yields significantly driven by local rainfall variation. These rainfall-driven shocks to agricultural productivity have substantial impact on local income of the poor and, due to their preference to consume lower-quality products, on the demand faced by smaller firms. Importantly, these shocks are orthogonal to productivity of firms in the manufacturing sector, allowing to isolate the effect of changes in composition of their customer base from other productivity driven changes (e.g., product quality) or changes to prices of their input factors.

The identification strategy rests on the credibility of two assumptions. First, rainfall shocks should change the demand from the poor consumers *relative* to the wealthier consumers. I conduct two tests to validate this assumption. In the first, I document that rain shocks affect the income of the poor without affecting the income of the richer income groups. In years of positive rain shocks the wages among the poor increase by 3 percent. No such effects are present for households employed outside agricultural sector. I then document that the poor have higher marginal propensity to consume than the rich. In response to an additional 1 Rupee received in income, households in lowest income group increase their consumption by 0.6 Rupee while households in highest income group increase their consumption only by 0.1 Rupee. Taken together, these estimates suggests that rainfall shocks serve as plausibly exogenous demand shifters for the poor households and affect their market size relative to the wealthier households. The second assumption is that firms should not be able to anticipate rain shocks in the current year based on past realizations of these shocks. If rain shocks are serially correlated across years, then firms could behave strategically today in anticipation of building up a customer base in the future. I explicitly test for and show absence of any serial correlation of rainfall across years in a district.

The estimates from the identification strategy indicate that in response to increase in rural income, driven by positive rainfall shocks, firms lowers their prices by 0.4 percent. I confirm that these effects are not driven by changes to the marginal costs of the firms and are instead due to firms lowering their markups. Specifically, average markups reduce by 1.2 percent in years of positive rain shocks, while the effect of rain shocks on marginal costs is positive (but statistically insignificant). If firms are lowering their markups in response to an increase in demand from poor households, then we expect that a same rainfall shock will induce larger demand effects in regions with higher share of agricultural population. Consistent with these differential demand effects, I show that prices and markups reduce more in districts with larger share of rural population. Importantly, these effects persist when I allow rainfall to have differential effects across districts based on the size of their rural population. This suggests that these price responses are driven by rain shocks affecting the composition of the consumer market rather than the size of the market. Finally, I show that the negative demand effects observed in wholesale prices are also present in retail prices for products sold in the village shops. In years of positive rain shocks, average retail prices for manufactured goods decrease by 0.3 percent.

Why would firms lower their markups in response to positive rainfall shocks, and more so in regions with larger share of agricultural workers? The demand composition channel above posits that an increase in demand from the poor households increases the demand elasticity only for firms that sell to both rich and poor households, forcing them to lower their markups and prices. Under assortative matching, these firms are proxied in my data by firms in the middle of the size distribution. To test for this channel, I examine how rain shocks affect the quantity sold and markups for firms across the size distribution within industries in a district. First, I show that the effects of positive rainfall shocks on quantity sold are monotonically decreasing with firm size. Positive rain shocks increases the quantities sold for firms in the lowest and middle of the size distribution, with no effects for firms in the upper range. Second, the same aggregate shock has a non-monotonic effect on prices and markups across the firm size distribution. Specifically, markups of mid-sized firms decrease by 1 percent in response to positive rainfall shocks, while markups of firms in the lower and upper ranges of the distribution remain unchanged. This is consistent with the hypothesis that better rainfall induces a change in the demand composition only for mid-sized firms by increasing their share of sales made to more price elastic consumers.

To provide further evidence in support of the demand composition channel, I first show that effect on prices and markups are unchanged once I control for marginal cost for the product. Controlling for marginal costs absorbs any changes in output prices resulting from movements along the demand curve. These movements can be generated from changes in supply-side environment of the firm such as improvement to its underlying productivity, or changes to efficiency of its labor force, or decrease in prices of factor inputs used by firms. Second, I show that these responses are only present in industries that cater more to local demand rather than national demand (proxied by tradability of the industry), and are stronger in sectors with larger scope for assortative matching between consumers and firms (proxied by higher differences in product quality). Third, as predicted by the theoretical model, I find that price effects are symmetrical in periods of both high and low rural demand: firms in the middle of size distribution lower their markups in years of better rainfall and increase them in drought years.

The intuition behind these observed lower markups during periods of increased demand is simple. Markup charged by a firm inversely depends on its *sales-weighted* average demand elasticity, where the weights are share of firms' sales made to each income group. Rain shocks disproportionately affect the demand from lower income groups and change the weighted demand elasticity, and hence markups, only for firms selling to both rich and poor households. These firms are proxied in my data by firms in the middle of the size distribution. Firms in lower range of size distribution sell primarily to the poor households, and therefore, while they observe a change in the level of demand, they do not observe any change in the composition of their demand. I show that this non-monotonic response of markups to demand shocks to the poor is unique to the demand composition channel, and provide empirical evidence inconsistent with alternative explanations of lower markups in periods of increased demand. Taken together, these evidence provide strong support for the demand-based markup channel.

Having established the relevance of consumer demand heterogeneity for markup variation across firms, I assess two implications of my results for cost of misallocation and cash transfer programs for the poor in developing economies. First, for assessing potential gains from resource reallocation, I rely on the argument that assortative matching generates stronger relationship between firm size and markup across sectors with higher degree of quality differentiation. Therefore, differences in the share of markup dispersion to TFPR dispersion across homogeneous and differentiated sectors would inform us on how much the demand-based markup channel contributes to the aggregate productivity dispersion. I find that markup dispersion contributes 8 percent more to TFPR dispersion across firms in quality differentiated sector relative to firms in homogeneous sector. This implies that the welfare gains from resource reallocation are lower than otherwise implied by standard models because high productivity and larger firms who charge high markups do so precisely because they face less demand elastic consumer base.

Second, the finding in this paper that prices decrease in response to higher rural income have implications for the aggregate welfare effects of government programs that provide support for low-income families. The implied elasticity of -0.15 of local prices to rural income implies that income transfers to the poor have a multiplier effect for the real consumption as a result of these price effects. Specifically, a 1 percent cash transfer to the poor income groups has 15 percent higher effect on real consumption of the poor under price effects as compared to the scenario when prices are assumed to be constant. Therefore, short-term social transfer programs targeting the poor (for example, through taxing the wealthier consumers) could reduce consumption inequality due to equilibrium effects of higher rural demand on prices through the demand composition channel.

These findings relate to two distinct, yet related, literatures. First, a recent and important empirical literature shows that markups vary systematically in the cross-section of firms and that they respond to changes in their operating environment. In particular, markups are high for exporters (De Loecker and Warzynski (2012); Atkin et al. (2015, 2017)), low for entering firms (Foster et al. (2008)), and decrease in response to increase in trade-induced competition (Edmond et al. (2015)). Recent work including De Loecker and Eeckhout (2018) and Autor et al. (2017) argue that markups have been rising for the larger firms, making them more important for the aggregate economy. My paper adds to the literature by providing a systematic source behind markup dispersion across firm size distribution. To the best of my knowledge, this paper is the first to empirically document the role of product market segmentation for systematic markup dispersion across firms. Few recent papers have documented similar patterns on assortative matching in the US retail sector (Faber and Fally (2017)) and in the Mexican manufacturing sector (Faber (2014)) to understand the distributional impact of trade liberalization. Relative to these papers, my paper assesses the importance of assortative matching for markup dispersion.

Second, following the seminal work by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), an extensive literature has focused on the factors driving misallocation. Numerous theories of misallocation have been advanced based on capital market frictions (Banerjee and Moll (2010); Buera et al. (2011); Midrigan and Xu (2014)), adverse selection in capital allocation (Fuchs et al. (2016)) or information frictions (David et al. (2016)). Accordingly, a large empirical literature has burgeoned in recent years estimating various sources of misallocation. In the context of the Indian economy, the evidence has ranged from degree of contract enforcement (Boehm and Oberfield (2018)), infrastructural investment (Allcott et al. (2016)), financial frictions (Banerjee and Duflo (2014); Bau and Matray (2019)); to differences in management practices (Bloom et al. (2012)) and licensing system (Aghion et al. (2008)). My paper provides a source of TFPR dispersion driven by markups that is unrelated to underlying distortions but rather manifests through differences in demand elasticities driven by income dispersion.[2] Apart from few notable exceptions (Peters (2018); Edmond et al. (2019); Haltiwanger et al. (2018)), existing literature typically treats markup dispersion as an exogenous firm-specific wedge that drives misallocation.

Similar to the spirit of this paper, few recent studies have attributed the observed dispersion in TFPR across firms into underlying economic forces unrelated to distortions. These include unobserved heterogeneity in physical productivity (Gollin and Udry (2018)), adjustment costs for dynamic inputs (Asker et al. (2014)), model mis-specification (Haltiwanger et al. (2018)) and measurement error (Bils et al. (2018)). My work contributes to this literature by empirically documenting and quantifying a new source of markup dispersion driven by consumer income (and preferences) dispersion.

The application in this paper is closely related to the literature on markup responses to demand shocks and contributes a new source of markup cyclicality. Existing papers in this area have analyzed the role of advertising costs (Chevalier et al. (2003)), search costs (Warner and Barsky (1995)), and costly external finance (Chevalier and Scharfstein (1996); Gilchrist et al. (2017)) for countercyclical markups in response to demand shocks. On the theory side, (Stiglitz (1984); Bils (1989)) are examples of theories of countercylical markups due to procyclical demand elasticities. My paper provides a source for such procyclical demand elasticity — changes to firms' *demand composition*. In this context, the closest study to this paper is Stroebel and Vavra (2018), which shows that lower demand elasticities induced by wealth effects for homeowners during the US housing boom allowed retailers to increase their markups. Relative to Stroebel and Vavra (2018), my paper argues that which part of income distribution gets more affected aggregate shocks determines the average markup responses.

Finally, a growing literature understands price dynamics across markets in developing countries. Recent work has documented the role of competition for price dynamics in agricultural markets (Bergquist (2019)) and among retailers (Cunha et al. (2018)) in low income countries. These papers take the level of competition as exogenous. My paper provides a complementary channel for price setting that manifests through heterogeneity in consumer demand: lower demand elasticity of wealthier households reduces the *effective* competition for firms producing better quality.

[2] There is a growing literature in international trade assessing the importance of markups. Empirical work analyzing the affect of markup heterogeneity for welfare gains from trade includes (but is not limited to) Edmond et al. (2015) and De Loecker et al. (2016). In contrast to my paper, these papers take markup variation as a source of misallocation as given. On the theory side, models of variable markups have been advanced including the work by Kimball (1995); Bernard et al. (2003); Melitz and Ottaviano (2008); Atkeson and Burstein (2008); Klenow and Willis (2016). My paper adds to this literature by providing a quality-based (i.e., a supply side) explanation for product market segmentation that generates higher markups for larger firms.

II Data Sources and Estimation

In this section, I start by describing the data sources used in the paper. I then outline the strategy for markup estimation that builds upon the production function estimation techniques from De Loecker et al. (2016). I then discuss the prevalence of geographically segmented consumer markets for manufacturing firms in India.

A. Data

Manufacturing firm-level data. Data on factory-gate wholesale prices come from the Annual Survey of Industries (ASI) maintained by the Ministry of Statistics. The basic unit of observation in the ASI is an establishment. I use the data from 1998 to 2009 that contain both consistent product level information and establishment location information during these years.[3] The sample frame for the survey is all manufacturing establishments in India that employ more than 10 workers. Establishments with more than 100 workers ("census" establishments) are surveyed every year, while smaller establishments are randomly sampled each year. The data contains establishment-level identifiers across years for both census and non-census establishments, allowing me to construct panel data for both types of establishments. I match the establishment-level panel data to a separate ASI cross-sectional data previously maintained by the Ministry, allowing me to obtain the location of all the plant at the district level.[4]

The ASI allows owners who have more than one establishment in the same state and industry to provide a joint return, but very few (less than 5 percent of my sample) do so, and the analysis is conducted at the level of the establishment. I treat each establishment as a separate firm but the results of the paper (discussed later) hold when I explicitly allow for only single-establishment firms.[5] ASI data enables me to track firm's product mix over time because Indian firms are required by the 1956 Companies Act to disclose product-level information on capacities, production, and sales in their annual reports. Firms report products in the ASI survey using ASI Commodity Classification (ASICC) codes which is the most refined level of product available in the dataset. There are approximately 2000 unique products in the data. As the "product" definition is available at highly disaggregated level, unit values are plausibly interpreted as prices. Firms in ASI report not only report total sales, but also sales and quantity sold down by product. I use this information to define unit-value as ((Total Sales Value)/(Total Quantity Sold)).[6]

[3]The ASI uses the accounting year, which runs from April 1 to March 31. We refer to each accounting year based on the start of the period; for example, the year we call "2000" runs from April 1, 2000 to March 31, 2001.

[4]A district is an administrative unit in India, with an average of 17 districts per state. A district is comparable to US county in size. On average, a district has approximately 2 million total residents.

[5]Therefore, going forward, I use the terms firms and establishment interchangeably. They always refer to the establishment.

[6]Prowess database is another data prominently used to conduct firm level research on Indian economy and also provides similar product-level information. Few caveats with the dataset makes it unsuitable for this study. First, Prowess only provide the location of the headquarters at the state level. Since the main source of variation for the shocks is at district level, the data is not particularly suited for this study. Second, Prowess database is useful for studying the behavior of large firms and hence we would completely miss the behavior of small firms in response to these shocks. Third, Prowess database is not well suited for understanding the firm entry and exit - an important outcome that I explore in this paper. See Goldberg et al. (2010); De Loecker et al. (2016) for more details on the Prowess database.

Retail Prices data. Retail Price Collection (RPC) data provides per-unit prices of retail goods across shops in all districts in India. This information is collected to construct Consumer Price Index (CPI) for rural population. By providing prices of goods across 256 product categories paid by consumers, RPC provides menu of prices faced by rural population across these products each month. The database does have few disadvantages compared to the ASI data. First, RPC only covers 256 broad product categories (unlike 2000 detailed product categories in ASI database) and is not as refined as the ASI product classification. Second, I don't observe the brand associated with a product and hence cannot use firm level information in RPC. However, RPC data has the advantage of providing price information at the monthly frequency instead of annual frequency of prices observed in ASI data. This is achieved by recording prices of the same commodity for the same shop at monthly intervals. Product consistency is maintained over time by ensuring the same product from the same shop is surveyed every time.[7] This allows me to follow the price of a product at monthly intervals between 2000-2009.

Rainfall data. I use the rainfall data collected by the University of Delaware to construct a time series of rainfall received across Indian districts since the year 1960. These data are gridded by longitude and latitude lines. In order to match these to districts, I simply use the closest point on the grid to the center of the district and assign that level of rainfall to the district for each year.

Other data. I use household level consumption data from Indian National Sample Survey (NSS) conducted between years 1998 and 2009 for information on per-unit price paid by households. The survey records total household expenditure and quantity bought by households across 256 product categories, which is used to construct the per-unit prices. The survey is a nationally representative repeated cross-sectional sample of about 500,000 households with sampling weights provided at the district-level.[8]

Information on wages and employment status comes from the NSS Employment Survey. I use household data from six annual repeated cross-section surveys conducted between the years 1999 and 2009. The survey asks the respondents details of their wages earned and number of days worked in past seven days by each member of household along with the sector in which they are employed. This is used to construct data on daily wage and employment status.

Finally, the agricultural data on district-level cropping patterns, crop prices and crop yields comes from the ICRISAT Village Dynamics in South Asia (VDSA) Macro-Meso Database. VDSA database is a compilation of various official government data sources. I use information on 15 major crops across districts in 19 states (containing 95 percent of the nation's population) from the years 1998-2009.[9]

[7] In case the shop no longer exists the survey moves to the next closest shop. In case the same product is no longer available, the closest substitute is selected to the replace the product in the survey. Notifications of these cases are provided in the data.

[8] The 256 product categories categories asked in the survey can be broadly classified into food, clothing and footwear, fuel and light, educational expenses, personal care items and durable goods.

[9] The 15 crops are barley, chickpea, cotton, finger millet, groundnut, linseed, maize, pearl millet, pigeon pea, rice, rape and mustard seed, sesame, sorghum, sugarcane, and wheat. These 15 crops accounted for an average of 73 percent of total cropped area across districts and years. I consider the data for *kharif* season which is the main crop season in India.

B. Measuring markups and marginal costs

This paper uses detailed micro-data on firms production to measure markups and marginal costs, building upon the approach pioneered by Jan De Loecker in his various contributions (De Loecker et al. (2016); De Loecker and Warzynski (2012)). Therefore, I relegate most of the technical details to Appendix B. The main benefit of this approach is that it allows me to measure firm's markups without having to take a stand on many aspects of the theory. This flexibility in this approach is particularly appealing in my setting as it allows to infer full distribution of markups across firms and products across different manufacturing sectors over time without imposing any parametric assumptions on consumer demand; or the underlying nature of competition; or assumptions on the returns to scale. The estimation relies on cost minimization providing the following expression for markups:

$$\mu_{jpt} = \theta^{v}_{jpt}\left(\alpha^{v}_{jpt}\right)^{-1}$$

where μ_{jpt} are the markups for firm j producing product p in year t. θ^{v}_{jpt} is the output elasticity for the product with respect to a variable input and α^{v}_{jpt} is the expenditure on that variable input as share of firm's revenue. As more than half of the plants in my sample produce more than one product, I specifically follow De Loecker et al. (2016) allowing for estimation of markups at firm-product level. This estimation procedure has few advantages relative to methods used on similar work in De Loecker and Warzynski (2012) that uses information on firms revenue and production inputs to estimate markup.

The availability of micro-data allows me to overcome two biases in markup estimates when compared to the existing work. First, the availability of physical output allows estimation less prone to measurement error. Data limitations have limited existing studies to rely on revenue based measure of output and productivity; and the use of industry-level price deflators for estimation. Second, I use expenditure on energy as the variable input in production. This is an important distinction relative to existing measures that rely on materials or labor as variable input. Developing economies such as India are plagued by weak credit enforcement and labor regulations; and thus, we cannot expect that adjusting these factor inputs is costless. The use of firm's electricity usage as the variable input in production arguably mitigates issues associated with fixed cost of input adjustment associated with input materials or labor.

C. Consumer markets for manufacturing firms

Many empirical settings consider separate geographical regions as separate markets. In the context of India, work from Topalova (2010); Leemput (2016) and Rotemberg (Forthcoming) provide evidence that geographically dispersed markets in India are not well-integrated.[10] There is also more direct evidence of localized customer markets for firms in developing economies. For example, using data from Sri Lankan firms, de Mel et al. (2009) show that the average percent of revenue coming from within 1 *km* of the

[10] Like many lower income countries, low market integration in India could be attributed to several reasons: people may travel less due to being more concentrated in dispersed, rural areas and having worse transportation infrastructure; it may be more difficult or costly for firms to advertise effectively; information aggregators (e.g., review sites) may be more limited; or contracting costs may be greater because civil courts are not as accessible or developed (Boehm and Oberfield (2018)); or informational frictions might be higher between retailers and their suppliers (Startz (2018)).This is consistent with the small average size of firms in developing economics, as documented in Hsieh and Klenow (2014) and Hsieh and Olken (2014).

business is 62% and the median is 75%. Similarly, using data on Indian boat manufactures, Jensen and Miller (2018) provide evidence of highly localized markets: the average percent of revenue coming from within 2 *kms* of the business is 76% and the median is 100%. While the ASI data — like most widely available manufacturing plants data from other countries — does not provide information on sales made by the firms dis-aggregated by domestic locations, I use two independent survey evidence in support of localized customer markets for manufacturing plants in India.

First, I use a survey data that solicits information from manufacturing firms about the problems faced by them during the last year of operation. The data specifically asks whether firms faced any problem due to "demand shrinkage". Appendix Table A.1 shows that firms report that they are 5% more likely to face drop in demand and 10% more likely to face any problem if the district they are located in faced a drought that year. These problems arise mostly from a drop in consumer demand that firms observe during periods of droughts. Second, I use information on expenses paid on transportation by firms as reported in the ASI data for the year 1998 (the only year in the survey for which this information was recorded). Firm's transportation expenses per-unit of sales is a proxy for how far the firm transport its products. Appendix Figure A.1 shows that these shares do not vary across the firm-size distribution: larger firms do not incur higher share of expenses on their transportation. If larger firms were instead selling larger share of their sales to farther districts as compared to smaller firms, we would expect larger firms to incur higher transportation expenses per-unit of sales.

These evidence show that (i) local demand for poor households is a significant component of demand faced by small- and medium-sized firms located in the same district, and (ii) firms across the size distribution catering to demand located within similar proximity of their production location. Taken together, this provides strong support for localized consumer markets for Indian manufacturing firms.

III Stylized facts

This section documents four stylized facts consistent with *assortative matching* — that is, the tendency of wealthier consumers to source their consumption from goods produced by larger firms. I document that (1) product level prices for manufactured goods are increasing in firm size (2) larger firms incur higher marginal costs and (3) larger firms charge higher marginal costs (4) richer households consume higher priced products.

1. Larger firms have higher per-unit price. Panel (a) of Figure I plots the relationship between per-unit price (in logs) charged by firms for their products and firm's labor force (in logs). The figure plots the residual value of log product price (y-axis) and log number of employees (x-axis) after controlling for district-product-year fixed effects, and therefore compares prices for firms located in the same district and producing the same product. The graph shows that larger firms charge higher per-unit price for their products.

2. Larger firms have higher per-unit marginal costs. Panel (b) of Figure I shows that larger firms incur higher marginal costs. The residual values along both axes follows from the last fact. Therefore, smaller firms have lower marginal costs than larger firms when the two are producing a product within the same product-group and are located in the same district. The same patterns hold if I consider average costs instead of marginal costs. Figure A.3 shows that larger firms use higher priced inputs, pay higher wages (per-unit labor) and are more capital intensive.

3. Larger firms charge higher per-unit markups. Panel (c) of Figure I documents one of the central findings of the paper: that larger firms charge higher markups for their products. The residual values along both axes follows as before. Hence, larger firms charge higher markups than smaller firms within the same product categories and located in the same district. Moreover, Figure II shows that variation in markups is higher in districts with more dispersion in household income.

Table II summarizes these correlations. Firms with one standard deviation (~ 0.75) larger labor-force have 7.2 percent higher sales prices, 3 percent higher marginal costs and 4.2 percent higher markups.[11] Columns (4)-(6) shows that higher marginal costs are associated with higher priced inputs, wages and capital intensity.[12] Table III shows that the positive relation of marginal costs and markups with firm size is stronger in sectors with greater scope of quality differentiation, proxied using Rauch (1999) classification of product differentiation. Column (1) shows that for firms with same size, markups are about 1.7 times higher in sectors with more quality differentiation. Column (2) shows that the positive relation between marginal costs and firm size is entirely driven by more differentiated sectors. Columns (3)-(5) show that this relation also holds for input prices, wages and capital intensity.[13]

4. Richer households consume higher priced products. Figure III documents the relationship between log per-unit value for a manufactured good consumed by households against log household income for the year 1993 (the last "thick" round of NSS consumption data available before 1998). The *y*-axis depicts the residuals of a regression of log unit price on region-by-product fixed effects, where region is either a town or village and is finer geographical unit than a district. The *x*-axis depicts the residuals of a regression of log household consumption on region-by-year fixed effects and household controls. Therefore, for purchases in the same region-by-product type, wealthier households pay higher average unit-value for the products they consume.

These stylized facts motivate a theoretical framework in which firm size is linked to differences in consumer expenditure across the income distribution through product quality. Specifically, Figure I (panel (a)) and Figure III suggest that rich and poor households systematically consume their products from firms with different sizes. Figure I (panel (b)) will serve to relate part of these observed price differences to

[11] In Figure A.4, I confirm that the firm size is positively correlated with both its output price as well as input prices within the informal sector using NSS data on unorganized manufacturing surveyed (UMS) in 2005-06. Unlike ASI data, which surveys firms in the organized sector, the NSS data survey smaller firms (average labor force of 3) in unorganized sector. However, the unavailability of panel data in UMS does not allow me to estimate markups and marginal costs.

[12] Appendix Table A.2 shows that these results are robust if I use firms' total sales or fixed assets as alternate proxy for its size. Results are also robust if I instead instead use the productivity parameter obtained from the production function estimation. Labor force is my preferred proxy as unlike sales or estimated productivity, it does not induce a measurement error in the independent variable that could be correlated with estimated markups and marginal costs.

[13] Using 1999-2000 NSS employment survey, Table A.3 documents that wages increases with worker's education level and firm size. It also documents that larger firms employ workers with more education, the best available proxy for worker's skills.

unobserved differences in product quality. Figure I (panel (c)) and Figure II will serve to relate remaining part of these observed price differences to estimated differences in price elasticities of demand across income groups. In the next section, I outline the model that formalizes this intuition, and generates testable prediction for markup responses to demand shocks across the income distribution.

IV Theoretical Framework

In this section, I present a simple model of quality choice in a setting with heterogeneous households in consumption and heterogeneous firms in production. The model serves two primary objectives. First, the model formalizes the central role for product quality for the assortative matching patterns documented in the previous section. Second, it generates testable predictions for how prices and markups would respond to demand shocks across the income distribution that I test empirically in Section V.

On the consumer side, households have heterogeneous quality valuations and demand elasticities, following Faber and Fally (2017). Specifically, when faced with identical prices, rich and poor households allocate their consumption expenditure differently across the quality ladder. The production side is a reduced-form version of the quality choice model of Kugler and Verhoogen (2011) that features endogenous input and output quality choice across heterogeneous firms.

A. Demand

Households are indexed by i. Each household derives utility from a product variety produced by firm j. Each firm produces a unique variety of product within the product group, and therefore j indexes both firms and products. Utility of household i is defined by:

$$U_i = \left[\sum_{j=1}^{J} q_j^{\phi_i} y_{ij}^{\frac{\sigma_i - 1}{\sigma_i}}\right]^{\frac{\sigma_i}{\sigma_i - 1}} \quad \text{s.t.} \quad \sum_j p_j y_{ij} \leq z_i$$

where each variety has a quality q_j, $\sigma_i > 1$ captures the demand elasticities across households, $\phi_i > 0$ if households' taste for variety and z_i is the level of households' income. I assume that household utility from consuming better quality increases with their income level such that $\phi_1 < \phi_2$ if $z_1 < z_2$. Consumers maximization their utility over y_{ij}, yielding the following demand curve for firm j's demand from consumer group i:

$$y_{ij} = q_j^{\phi_i(\sigma_i - 1)}\ p_j^{-\sigma_i} \left(\sum_{j=1}^{J} p_j^{1-\sigma_i}\right)^{-1} z_i \tag{1}$$

These preferences are common across households but non-homothetic as the utility from consumer goods depends on income level z_i as well as individuals taste for quality ϕ_i and demand elasticity σ_i. There are few advantages of working with this structure. First, we keep the price elasticity of demand to be constant within income groups but allow them to vary across income groups. This allows me to retain the CES preferences structure, while still allowing to understand the implication of consumer heterogeneity for prices and markups across firms. Second, I impose no restriction on how price elasticity of demand depends on income and rather estimate it using the data.

Household i's expenditure on good j is given by x_{ij}:

$$x_{ij} = q_j^{\phi_i(\sigma_i - 1)} \; p_j^{1-\sigma_i} \left(\sum_{j=1}^{J} p_j^{1-\sigma_i} \right)^{-1} z_i \tag{2}$$

Comparing two varities j and k gives the following relation between their share of expenditure by household i, their prices (p_j, p_k) and qualities (q_j, q_k)

$$\log \frac{x_{ij}}{x_{ik}} = (1 - \sigma_i) \left[\log \frac{p_j}{p_k} - \phi_i \log \frac{q_j}{q_k} \right] \tag{3}$$

Notice that in the model σ_i does not vary across products. Therefore, I can estimate σ_i from above expression by only considering goods with no quality differentiation (for which $\Delta \log q_j = 0$). This is important because estimating σ_i based on products with differences in quality would generate bias in the estimates as for such products $\Delta \log q_j \neq 0$.

Proposition 1. *Average quality of the household's consumption basket increases in quality valuation ϕ_i.*

Proof. Define $s_{ij} = \frac{p_j x_{ij}}{\sum_j p_j x_{ij}}$ as share of household i expenditure on product j. Taking derivative of s_{ij} with respect to quality evaluation ϕ_i gives us : $\frac{ds_{ij}}{d\phi_i} = (\sigma_i - 1)(\log q_j - \sum_j \log s_{ij} \log q_j)$. This implies that household's expenditure shares within product groups increase in ϕ_i for products with above average quality, and decrease in ϕ_i for below average quality products. As a consequence, households with lower quality evaluations ϕ_i (i.e. poorer households) allocate higher share of their consumption expenditure to products with lower quality. ■

B. Production

On the production side, each firm produces a single variety of product subject to a fixed cost F. The profit function for the firms is given by

$$\pi_j = p_j y_j - c'(y_j) y_j - F = \left(1 - \frac{1}{\mu_j} \right) x_j - F$$

where p_j is the price of the product j, y_j is quantity sold by firm, $c(y_j)$ is the total cost and x_j are the total sales made by the firm (therefore $x_j = p_j . y_j$). I assume that marginal costs are increasing in firm's product quality. Specifically, following Kugler and Verhoogen (2011) as motivation, I assume that the functional form for marginal costs by assuming the total cost of firm is increasing in its quality and decreasing in productivity (λ_j) and is given by $c(y_j; q_j, \lambda_j) = \frac{q_j^\alpha y_j}{\lambda_j} + k q_j$. Therefore, marginal cost for the firm is $c'(y_j) = \frac{q_j^\alpha}{\lambda_j}$ and is increasing in the quality of the product. Letting μ_j be the markups defined by $p_j = \mu_j c'(y_j)$. Substituting this in the expression (2) gives the following expression for demand curve

$$x_{ij} = q_j^{(\sigma_i - 1)(\phi_i - \alpha)} \; \mu_j^{1-\sigma_i} \; P_i^{-1} \; \lambda_j^{(\sigma_i - 1)} \; z_i \tag{4}$$

where $P_i = \left(\sum_{j=1}^{J} p_j^{1-\sigma_i}\right)$ is the price index faced by consumer group i. Total sales made by firm j is given by $x_j = \sum_i x_{ij}$.

C. *Firm's Optimization*

In equilibrium consumers maximize utility. Firms take the consumers demand curve (4) as given and choose their markup, quality and quantity to maximize their profits, subject to free entry (zero profits). As all firms face same optimization problem, I suppress subscript j for convenience:

$$\max_{\mu,q} \ \pi(\mu) = \left(1 - \frac{1}{\mu}\right) \sum_i x_i - F$$

where $x_i(\mu, q, \lambda, z)$ is the sales made by firm to consumer group i.

Proposition 2. *Product quality of a firm is increasing in its sales.*

Proof. Optimal quality produced by firm is given by:

$$q_j = \frac{1}{k} \left[\left(\frac{\tilde{\sigma}_j - 1}{\tilde{\sigma}_j} \right) \ x_j \ \left(\hat{\phi}_j - \alpha \right) \right] \tag{5}$$

where $\tilde{\phi}_j$ average quality for firms j given by $\hat{\phi}_j = \left[\frac{\sum_i (\sigma_i - 1) \ \phi_i \ x_{ij}}{\sum_i (\sigma_i - 1) \ x_{ij}} \right]$. Equation 5 shows that product quality of the firm is increasing in its sales. Intuitively, this is because for two firms with the same consumer base, the larger firm would be more profitable for a given quality upgrade. ■

Therefore, Proposition 1 and 2 imply product quality creates a sorting among households in their expenditure share and among firms in their size. As larger firms are better at producing higher quality products, wealthier households have larger share of their consumption expenditure from larger firms: a pattern I refer to as *assortative matching* on product quality. As marginal costs are increasing in the underlying product quality, this implies that larger firms have higher marginal costs (stylized fact 2) and wealthier households pay more for the products they consume (stylized fact 3).

The first order condition from equation 2 also provides us with the following expression of *firm-level* markup:

$$\mu = \frac{\sum_i \sigma_i x_i(\mu, q, \lambda, z_i)}{\sum_i (\sigma_i - 1) x_i(\mu, q, \lambda, z_i)} = \frac{\tilde{\sigma}}{\tilde{\sigma} - 1} \tag{6}$$

where $\tilde{\sigma}$ is the average demand elasticity for the firm given by

$$\tilde{\sigma} = \frac{\sum_i \sigma_i x_i(\mu, q, \lambda, z_i)}{\sum_i x_i(\mu, q, \lambda, z_i)} = \sum_i \sigma_i \psi_i(\mu, q, \lambda, z_i) \tag{7}$$

where $\psi_i(\mu, q, \lambda, z_i) = \frac{x_i(\mu, q, \lambda, z_i)}{\sum_i x_i(\mu, q, \lambda, z_i)}$ is the share of firm's sales made to the consumer group i. Equation 6 allows for a new source of markup variation across firms: firms face heterogeneous market demand curves depending on composition of consumer income group i demanding their products. This composition is dictated by the matching among consumers and firms, under which the rich consumers have higher share of better quality products in their consumption basket.

Prediction 1. *Under assortative matching, decreasing demand elasticities with income levels implies that markups charged for firms are increasing in their size.*

Proof. Following Proposition 1, ψ_i is decreasing in quality for poor households (i.e. households with lower quality evaluations). Thus, ψ_i for poor households is higher for smaller firms as compared to larger firms. Large σ_i for poor households in equation 6 implies that firms' demand elasticity firm is decreasing in its size. Therefore, smaller firms charge lower markups than larger firms. This prediction is consistent with stylized fact 2 (panel (c) of Figure I). ■

D. Implications for Firm-Level Prices to Income Shocks

I now reintroduce subscripts for firm and time. Let z_{pt} be demand shocks to the poorest income group. Taking logs and derivative for markups in equation 6 with respect to $\log z_{pt}$:

$$\frac{d\log\mu_{jt}}{d\log z_{pt}} = \frac{-1}{\tilde{\sigma}_{jt}(\tilde{\sigma}_{jt}-1)}\frac{d\tilde{\sigma}_{jt}}{d\log z_{pt}} = \frac{-1}{\tilde{\sigma}_{jt}(\tilde{\sigma}_{jt}-1)}\sum_k \sigma_{kt}\psi_{kt}\frac{d\log\psi_{kt}}{d\log z_{pt}}$$

Solving and replacing for $\frac{d\log\psi_{kt}}{d\log z_{it}}$ gives us:

$$\frac{d\log\mu_{jt}}{d\log z_{pt}} = \frac{-\psi_{ij}\times(\sigma_p-\tilde{\sigma}_{jt})}{\tilde{\sigma}_{jt}(\tilde{\sigma}_{jt}-1)} = \frac{-\sum_{k\neq i}(\sigma_p-\sigma_k)\psi_{kj}\psi_{ij}}{\tilde{\sigma}_{jt}(\tilde{\sigma}_{jt}-1)} \tag{8}$$

It is clear that markups responses to income shocks to the poor are dependent on (i) share of sales made by firm across income groups ψ_{kj} (ii) difference between average demand elasticity of the poorest income group relative to other income groups $(\sigma_p-\sigma_k)$ (iii) average demand elasticity of the firm $\tilde{\sigma}_{jt}$.

Prediction 2. *Firms lower their markups in response to demand shocks to the poor.*

Proof. Poorest households have highest price elasticity of demand (i.e. $\sigma_p > \sigma_k > 1 \;\; \forall\, k$). Combined with the fact that $\psi_{kj} \geq 0 \;\; \forall\, k$ and $\tilde{\sigma}_j > 1$, equation 8 implies that $\frac{d\log\mu_{jt}}{d\log z_{pt}} <= 0$. Thus, markups either decrease or stay the same in response to demand shocks to the poor. ■

Define $\zeta_{pjt} \equiv \frac{d\log\mu_{jt}}{d\log z_{pt}}$ as the elasticity of firm j's markup to demand shocks to the poor in year t. We are interested in how ζ_{pjt} varies with share of firm j's sale made to the poor (i.e. ψ_{pjt}).

Prediction 3. *Demand shocks to the poor have a non-monotonic effect on markups across the firm-size distribution.*

Proof. This follows in two steps, details for which are provided in Appendix E. First, there exists a unique $\psi_{pj} \in [0,1]$ for which the function $\frac{d\zeta_{pjt}}{d\psi_{pjt}}$ takes the value of 0. Second, the function $\frac{d^2\zeta_{pjt}}{d\psi_{pjt}^2}$ is strictly positive. This implies that the elasticity of markups to demand shocks to the poor has a non-monotonic relation with respect to firm size.[14]. ■

[14] As per Proposition 1, ψ_{pjt} is monotonically decreasing in size of the firm and therefore the relation of ζ_{pjt} over firm size distribution follows the same relation between ζ_{pjt} and $(1-\psi_{pjt})$.

Let's take a simple example to illustrate this channel. Let there by only two consumer groups in the economy - the poor and the rich. As before, let z_{pt} be the income shock to the poor population. In context of equation 8, we can derive the markup elasticities to the income shock z_{pt}:

$$\frac{d\log\mu_{jt}}{d\log z_{pt}} = -\frac{(\sigma_{poor}-\sigma_{rich})}{\tilde{\sigma}_{jt}(\tilde{\sigma}_{jt}-1)} \times \psi_{poor,j,t} \times (1-\psi_{poor,j,t}) \tag{9}$$

Figure VI plots $\frac{d\log\mu_{jt}}{d\log z_{pt}}$ from specification 9 as a function of share of sales made by firm to poorest income group, for various values of $(\sigma_{poor},\sigma_{rich})$. Two findings stand out. First, notice that the markup elasticity is zero in absence of any heterogeneity in demand elasticities (i.e. $\sigma_{poor}=\sigma_{rich}=\sigma$). This is equivalent to the CES preferences structure. Second, markup elasticity is strictly convex relation with respect to share of sales made the firm to the poor $\psi_{poor,j,t}$. On either extremes, firms that make all of their sales to poorest households ($\psi_{poor,j,t}=1$) and firms that make all none of their sales to poorest households ($\psi_{poor,j,t}=0$) do not change their markups. Moreover, the curvature of the function is increasing in differences in demand elasticities of the poor and the rich households. Intuitively, demand shocks to poor raises the share of sales made to the poor for firms that cater to a heterogeneous consumer base. This in turn leads these firms to pay more attention to the demand elasticity of its more price elastic consumer base, and hence lowering their markups.[15]

E. Discussion

The model has imposed number of other restrictive assumptions including a specific CES demand system. The particular demand system and production functions provide simple, tractable solutions and comparative statics. However, these functional forms are not crucial for the paper and the predictions hold under CES demand with non-monopolistic competition (based on Atkeson and Burstein (2008)) that generates endogenous demand elasticities faced by firms from different income groups (Appendix Section F); or under alternate demand demand system based on explicitly additive consumer preferences (Appendix Section G). Finally, Appendix Section H shows the demand composition channel in a general framework without imposing the assortative matching channel. Hence, quality sorting is one dimension on which one could expect demand shocks to have asymmetric effect across the firm-size distribution.

The model also assumed that firms cannot price discriminate across different income groups.[16] While different retailers might charge different prices for the same product, it is unlikely that manufacturing firms would. Price differentiation *across* retailers could be driven by differences in their operating costs and it is hard to argue that retailers can price discriminate *within* the store across income groups. Additionally, the model has assumed that complete pass-through from wholesale prices (i.e. manufacturers' prices) into retail prices. Therefore, I restrict the role of retailers as passive price-takers. Under this

[15] Under the assumption that demand shocks do not affect marginal costs i.e. $\frac{d\log mc_{jt}}{d\log z_{pt}}=0$, z_{pt} affects prices only through markups. Specifically as $\log p=\log\mu+\log mc$, $\frac{d\log mc_{jt}}{d\log z_{pt}}=0 \implies \frac{d\log p_{jt}}{d\log z_{pt}}=\frac{d\log\mu_{jt}}{d\log z_{pt}}$.

[16] This assumption is similar to firms not operating multiple product lines. This is different from the assumption in the work of Verhoogen (2008); Bastos et al. (2018) in which exporting firms operate different product lines for products exported to different countries. This paper focuses on non-exporting firms that cater to domestic demand and are less likely to operate multiple product lines for different income groups.

assumption, the demand elasticity faced by wholesalers is same as that faced by retailers.[17]

V Empirical Methodology

In this section, I propose an identification strategy to test the model's predictions. The objective is to understand how firms adjust their prices in response to changes in demand. However, equation 4 suggests any correlation between price changes and quantities will not identify the causal effect of demand because of (i) reverse causality: high quality products could observe an increase in their demand, that is causality might run from prices to quantities; and (ii) omitted variable bias: changes along the demand curve i.e. changes to marginal costs of production could change firms' prices and therefore the demand for their products; and (iii) measurement error: estimates could be mechanically negative as prices are calculated as product revenue divided by quantity sold for that product.

To address these identification issues, I use changes in consumer demand driven by changes to household income due to local rainfall fluctuations. The idea is the following: based on equation 4, quantity demanded by a consumer group i over time (i.e. Q^i_{jt}) is increasing in the income for that group z_{it}. To see this formally, taking logs and differencing equation 4 (where $\Delta y_t = y_t - y_{t-1}$):

$$\Delta \log Q^i_{jt} = (\sigma_i - 1)\left[\phi_i \Delta \log q_{jt} - \left(\frac{\sigma_i}{\sigma_i - 1}\right)\Delta \log p_{jt}\right] + \Delta \log P_{it} + \underbrace{\Delta \log z_{it}}_{\text{Demand Shifter}} \tag{10}$$

The last term shows that we can obtain variation in demand from changes in income for households over time. As $Q_{jt} = \sum_i Q^i_{jt}$, these income changes affect the demand for firms Q_{jt} depending on share of firm's sales made to consumer group i. Local rainfall fluctuations, by significantly affecting the rural income, are ideal instruments for changes in consumer income and serve as quasi-random demand shifter for firms that cater to these consumers.[18] The next section provides background and details on rainfall shocks in rural India. I then describe the instrumental variable strategy that uses these rainfall fluctuations to study how firms adjust their prices to changes in their demand.

A. *Rainfall shocks in India*

Agricultural households in India face extremely high income volatility across years. 70 percent of farmed area in India is rain-fed; and thus the agricultural production is considerably dependent on rainfall. Rainfall exhibits significant variation across districts and over years, and are an important driver of agricultural productivity and rural income.[19] In this context, local rainfall fluctuations generate income

[17] As mentioned in Nakamura and Zerom (2010), incomplete pass-through can be driven by combination of retailers' markup adjustment, local costs and costly price adjustment. Analyzing the pass-through of costs shocks to wholesale and retail prices in the US coffee market, the authors find support for large local costs and markup adjustment. Moreover, they find evidence that the pass-through occurs at the wholesale rather than the retail level.

[18] Using weather-induced income also has an additional advantage over other measures of local income changes (for e.g., industry level wage growth) as the latter could be driven by changes in price levels in the local economy. To see this formally, we can decompose $\Delta \log z_{it}$ into a function of aggregate prices ($f(P_{it})$) and a residual variation independent of prices (ε^z_{it}): $\Delta \log z_{it} = f(P_{it}) + \varepsilon^z_{it}$. Rain shocks Shock$_{dt}$ affects the residual variation in rural income group ε^z_{it}.

[19] Similar to many other developing countries, majority of the poor in India are employed in the agricultural sector. About 66 percent of males and 82 percent of females in rural India report agriculture (as either farmers or laborers) as their principal

fluctuations for the rural households, and increase the market size for firms that cater to the demand of these consumers. While there is an extensive literature in economics documenting the adverse impact of droughts on agricultural output and rural wages, I also confirm these findings in Section VI. I find that positive rainfall fluctuations increase (and droughts decrease) rural wages, providing confidence that rainfall shocks are indeed a income, and thus demand shifter for poor households.

I define a positive shock if the annual rainfall measure is above the 80^{th} percentile and negative shock as rainfall measure below the 20^{th} percentile within the district. The "positive" and "negative" shocks should not be taken in an absolute sense as I am not comparing districts that are prone to higher rainfall to those that are prone to lower rainfall. These are simply high or low-rainfall years for each district during 1960-2009. For the analysis, I define "rain shock" as equal to +1 for positive shock, -1 for negative shock, and 0 otherwise. These are similar to the definitions employed in Jayachandran (2006); Kaur (2018). Figure VII shows the distribution of these shocks across Indian districts over the period of 12 years. The extensive variation in rainfall across time and space is evident from the figure.[20]

B. Identification Strategy

I now use variation in local income generated through deviations in local rainfall in the following standard IV framework:

$$\begin{aligned} \log p_{jpdt} &= \beta \text{ Shock}_{dt} + \alpha_{jp} + \alpha_{pt} + \gamma \tilde{X}_{jpdt} + \eta_{jpdt} \\ \log Q_{jpdt} &= \lambda \text{ Shock}_{dt} + \alpha_{jp} + \alpha_{pt} + \zeta \tilde{X}_{jpdt} + \varepsilon_{jpdt} \end{aligned} \tag{11}$$

where $\frac{\beta}{\lambda}$ provides consistent estimates of price elasticity to quantity under suitable identification conditions (discussed in details below). $\log p_{jpdt}$ is the year t price (in logs) for product p produced by firm j located in district d. Shock_{dt} are local rain shocks in district d and year t as defined above. $\tilde{X}_{jpdt}$ is a vector of firm-level and district-level controls $\tilde{X}_{jpdt} = (\log mc_{jpt}, X_{jpdt})$. As products produced by different firms could differ across various characteristics, I include α_{jp} which absorbs any time-invariant firm-product unobservables (for example, any constant quality differences). The presence of interaction term α_{pt} controls for product-specific inflation rates and any macro-economic shock at the product level (for example, changes in national tariffs for particular products). The firm-product and time dummies therefore capture permanent differences in price levels among different products and common time-trends in prices.

Whenever specified, I include as a control firms' estimated marginal cost of production ($\log mc_{jpt}$)

economic activity (Mahajan and Gupta (2011)). The relationship between agricultural employment and income distribution across districts is evident from Figure A.2. The figure shows that average income in the district is systematically decreasing in its share of population employed in the agricultural sector.

[20]The results in the paper does not depend on the choice of this measure of rainfall shock. The motivation of using this measure is twofold: First, as shown in Figure A.5, there non-linear relationship between rainfall deviations in a year and agricultural outcomes including crop yields, agricultural employment rate and agricultural wages. Thus, the use of this discrete measure increases the precision and power of the estimates. Second, the measure allows to maintain consistency thus allowing me to measure my elasticity of agricultural productivity and wages to the existing literature. I test the results with alternate measure of rainfall deviation. Appendix Table A.5 shows that the main results are qualitatively the same when I use alternate cutoffs for the shocks or use continuous measure of rainfall deviations instead.

to absorb any biases in the estimates due a movement along the demand curve (rather than a shift in the demand curve). This addresses any omitted variable bias by absorbing any component in the error term that might be correlated with both price changes and quantity produced. Finally, X_{jpdt} is a vector of time-varying district and firm level controls. Firm controls include firm-level controls of lagged sales-to-asset ratio, cost of goods sold-to-asset ratio and inventory-to-sales ratio. District-level controls include weighted rainfall deviation of all other districts, where the weights are based on the distance between the origin district and the final district.

Ideally, I would like to run the specification 11 using income shocks to the consumer base of each firm. However, I do not observe data on total rural income in the district or firm's actual consumer base. Given the lack of first stage, most of the empirical analysis will be presented in terms of reduced form relationship between the dependent variables and rainfall fluctuations as an intent-to-treat setting:

$$\log y_{jpdt} = \beta \;.\; \text{Shock}_{dt} + \alpha_{jp} + \alpha_{pt} + \gamma X_{jpdt} + \eta_{jpdt} \tag{12}$$

where y is either prices, markups or marginal costs. The reduced form coefficient β in the specification is straightforward to interpret as the elasticity of the response of firm prices, markups and marginal costs (depending on the outcome variable) to rain shocks in district d across various years.[21]

Identification Assumptions. Consistent estimation of β in specification 11 requires two conditions to be satisfied: instrument relevance, that is, Shock_{dt} and $\log Q_{jt}$ should be correlated; and instrument relevance, that is, Shock_{dt} is uncorrelated with η_{jpdt}. Relevance can be directly tested in the data (the first stage). First, local rainfall deviation should be strongly correlated with the local income and therefore the quantity demanded (i.e. first stage). I provide two supporting evidence that rainfall shock indeed changes the relative market size from the poor population. In Section VI, I first document that rainfall shock does not effect the wages of the population employed outside agricultural sector during the monsoon months. I then document that poor have higher marginal propensity to consume out of temporary income changes. This finding is consistent with the literature which shows that households exhibit high marginal propensity to consumer (MPC) out of transitory income shocks and that it is higher for poor relative to the rich (Patterson (2018)). Figure IV reports the distribution of MPC across income distribution.[22] For same increases in income (and conditional on prices), quantity demanded increases more for the population with higher marginal propensity to consume. Therefore, income changes for wealthier households should not induce a significant change in demand from that group. This follows from the relation: Δ Quantity Demanded $= \Delta$ Income $\times$ MPC.

[21] Specification 12 could also be expressed in first differences framework by differencing it across time-periods: $\log p_{jpdt} - \log p_{jpd,t-1} = \beta(\text{Shock}_{dt} - \text{Shock}_{d,t-1}) + \alpha_{pt} + \zeta_{jpdt}$. The coefficient β has the same expected value in both specifications. Specification 12 has the flexibility of not relying on the data from consecutive years — which helps my analysis as the primary database (ASI) is from repeated cross-section database of firms.

[22] I follow Gruber (1997) and calculate the MPC using the observed drop in consumption upon unemployment. Using a monthly panel data on 100,000 households from CMIE consumption data, I estimate the following regression for household i in district d and region r at month t: $\Delta \log x_{ivt}(z) = \alpha(z)\, \Delta \log y_{ivt}(z) + \beta_i + \gamma_{vt} + \varepsilon_{ivt}$, where β_i is the household fixed effect and γ_{vt} is a region-year fixed effect that captures the total resources available in the region-month and aggregate shocks in month t. As the regression is run on a panel data at household-month level, the coefficient α is identified of the variation in *within* household income living in the same region in a month.

Second, rainfall deviations should satisfy exclusion restriction. That is, it should affect prices only through changes in demand. While this assumption cannot be directly tested, I provide several pieces of evidence in the following section that support this correlation. I first show that that rainfall deviations are transitory in nature and affect the quantity demanded by the poor without changing their long-run price elasticity. To validate this assumption, I test for serial correlation of rainfall within districts because serially correlated rainfall shocks could lead to permanent effects and induce permanent shifts in the price-elasticity of demand. For example, poor households can become less price-elastic if higher income in the current year due to good rainfall is predictive of higher income in the future years. Moreover, if rainfall shocks this year are correlated with rainfall shocks next year, it is difficult to tell the extent to which is are picking up the effects of a single contemporaneous shock or multiple years of rainfall shocks. Table A.6 column (1) test for serial correlation based on AR(1) specification and column (2) test for serial correlation using an AR(2) specification.[23] As results in both columns show, I find no evidence of serial correlation in rainfall shocks across years in my sample (Columns (1) and (2)) as well as outside the time period considered in my sample (Column (3)-(4)).

VI Results

This section presents the main empirical results of the paper. I start by estimating the demand elasticities across the income distribution and document that poor households are indeed more demand elastic than the rich households. I then exploit the spatial and temporal variation in rainfall fluctuations to show the affect of local rainfall on local income for population in the agricultural sector. I then analyze the effects of rain shock induced demand shocks on prices of manufactured goods on average and decompose them into markup responses versus changes to marginal costs. I decompose these average effect into responses due to changes in demand composition versus changes in the level of demand, and provide evidence consistent with effects driven by changes to composition of demand. I then provide evidence on the demand composition channel by analyzing the differential effects of rain shocks on markups across the firm size distribution. Finally, I document similar price responses in retail prices across goods sold in shops across Indian villages.

A. *Estimates of demand elasticity across income groups*

I start by estimating price-elasticity across different income groups based on the equation 3:

$$\log\left(\frac{x_{irt}(z)}{x_{jrt}(z)}\right) = \alpha_{zir} + \beta(z)\log\left(\frac{p_{irt}}{p_{jrt}}\right) + \nu_{ijrt}$$

where i is a product variety, h is a household in region r and income group z surveyed in year t. $x_{irt}(z)$ is the household expense on particular variety sold at price p_{irt}. As $\beta(z) = 1-\sigma(z)$, the above specification provides us with an estimate of elasticity by income group $\sigma(z)$. Following Li (2018), I benchmark $j = 0$

[23] To test for serial correlation in rainfall, I run the following specification across district-year panel data: $\text{RainDeviation}_{dt} = \alpha_d + \alpha_t + \beta_1 \text{ RainDeviation}_{d,t-1} + \beta_2 \text{ RainDeviation}_{d,t-2} + \varepsilon_{dt}$; where $\text{RainDeviation}_{dt}$ is the rainfall deviation in district d and year t form the median rainfall of the district since 1960.

with the most frequent commodity consumed in a region, giving the following estimation equation:

$$\Delta \log x_{irt}(z) = (1 - \sigma(z))\Delta \log p_{irt} + \alpha_{zir} + \alpha_{zrt} + \nu_{zirt}$$

The OLS estimate of $\sigma(z)$ will be potentially biased due to unobserved taste shocks in the error term could be correlated with price changes. I address this issue by intrumenting local prices $\Delta \log p_{irt}$ with state-level leave-out mean price changes $\frac{1}{N-1}\sum_{j \neq i} \Delta \log p_{jrt}$. Figure V shows that price-elasticity of demand is decreasing in income levels. Table A.4 documents the estimates for price elasticities across income groups after controlling for household characteristics. The price-elasticity of demand of the lowest quintile of the income distribution is 1.7 times higher than that of the richest quintile. These average effects are consistent with Li (2018). [24]

B. Impact of rain shocks on rural income

Column (1) and (2) of Table IV shows the effect of rain shocks on agricultural productivity and revenue: rain shocks impact agricultural yields by 5% which is in line with Jayachandran (2006).[25] These results show that rain shocks are indeed productivity shocks in context of the agricultural sector. Column (3)-(4) of Table IV shows the effect of rain shocks on incomes of the poor: daily wages of farmers and agricultural workers increase by 2.5 percent and 4 percent respectively. At the same time, rain shocks do not effect on wages during the month of rainfall incidence for households employed outside agricultural sector (Column (5)). Consistent with the effect of rain shocks on labor market outcomes, Column (6) and (7) shows that the unemployment rate decreases by 0.3 percentage point and 0.6 percentage point for farmers and agricultural laborers, respectively.

Taken together, this suggest that rain shocks generate variations in income from the poor consumer and thus the relative size of their demand in the local economy. I now present the results on how firms adjust their prices and markup in response to these rainfall induced demand shocks.

C. Effect of rain shocks on manufacturing firms' output prices

In this section I use the identification strategy described in section V to estimate the effect of rainfall-induced demand shocks on the wholesale prices charged by firms. Table V presents our main results and reports the OLS, IV and Reduced Form coefficients from specification 11. All columns include log of

[24] In Appendix Section I, I use survey data from households' time spent on shopping to show alternate evidence consistent with excess price sensitivity of the poor. Poorest households report spending significantly more time in their shopping activities compared to richer households. More time spent in shopping could be reflective of searching for lower prices due to excess price sensitivity or lower opportunity cost of time. Although, more time spent on shopping is not exactly equivalent to higher demand elasticity, it certainly is among the measures closer to the concept.

[25] Specifically, I run the following specification:

$$y_{dct} = \beta \times \text{Shock}_{dt} + \alpha_{dc} + \alpha_{ct} + \gamma' X_{dt} + \varepsilon_{dct}$$

where $yield_{dt}$ is the average yield (output per hectare) in district d for crop c and year t across fifteen major crops in India and α_{dc} and α_{ct} are the district and year fixed effects respectively. Shock_{dt} are rain shocks respectively as defined above. Moreover, a positive shock increases the district's agricultural yield by 5.4% whereas a negative shock decreases the district's agricultural yield by 11.6%.

marginal cost as a control that absorbs any movement along the demand curve. Column (1) shows that average quantities sold by manufacturing firms increase by 1.2 percent in years of positive rain shocks. Column (2) shows that a 10 percent increase in quantity sold decreases prices by 0.6 percent. In Column (3), I instrument for quantity sold with rain shocks. The estimated elasticity of prices to quantity sold increases to -0.4 suggesting that a 10 percent increase in quantity sold decreases prices by 4 percent.

The IV coefficients are around six times larger than the corresponding OLS estimates. One potential explanation for the downward bias in the OLS coefficients is unobservable shift of the demand curve that might increase prices as well as quantity sold by firms. In particular, it could be that common economic shocks in the district increases the demand for goods for all firms as well as the reservation wage in manufacturing sector. Or it could be that firms lower prices in response to some external decrease in marginal costs, which in turn increases the demand. Under such cases, one would expect the OLS coefficient to display an upward bias of an increase in quantity sold on prices relative to the IV coefficient.

Finally, Column (4) presents the reduced form estimates of rain shocks on wholesale prices. The size of the estimated coefficient indicates that firms lower their prices by 0.5 percent on average in response to positive rain shocks.

Next, I show that the results presented above are robust of inclusion to various controls, as documented in Table VI. As described in section V, I use the reduced form estimation (specification (12)) as my baseline specification and conduct various robustness based on that. Column (1) shows that firms lower their prices by 0.45 percent in years of positive rain shocks. Column (2)-(7) shows that the estimates are robust to various robustness checks. In Column (2), I include firm level controls including cost to assets and lagged inventory to assets as proxies for changes to firm cost (described in Section V). In Column (3), I restrict the analysis to only single plant establishment as multi-plant establishment might not be responsive to local shocks as much as single-plant establishments. In Column (4) I include the market access controls with is a weighted average rainfall deviation for each district d' connected to district d, where the weights are proportional to the distance between the two districts. Column (5) allows market access to have different impact based on whether other districts are in the same state as district d. Column (6) allows for include for past two-years of rain shocks to allow for any effects from lagged changes in demand. Finally, in Column (7) I allows for inclusion of controls from Column (2),(5) and (6). As can be seen, addition of these controls to the regression has no significant effect on average effect of rain shocks on prices.

D. *Variable markups or changes to marginal costs?*

The results above provide evidence of strong response of wholesale prices to rainfall-induced demand shocks. By definition, changes in prices can be driven by firms changing their markups or firms' pass-through of changes in their marginal costs. While studying either channel is interesting in itself, I provide evidence that the observed price responses are driven due to firms changing their markups instead of them passing through changes in their marginal costs. Table VII decomposes the price effects into underlying markups versus marginal cost changes. Column (1) documents the average price responses from before. Column (2) shows that firms lower their markups in years of positive rain shocks: the average markups decrease by 1.15 percent in years of positive rain shocks. When I include firm-level controls for cost-to-assets and inventories-to-assets, the effects increases to -1.24 percent (Column (5)). The estimates remain robust to inclusion of past years shocks as documented in Column (7)-(8). Column (3),(6) and (9) repeat the exercise for marginal costs. While marginal costs seem to increase for firms in periods of better rainfall, the estimates are not statistically significant. Taken together, these findings suggests that firms lower their markups in response to positive rain shocks. This is consistent with the hypothesis that rain shocks, by increasing the relative demand from more price-sensitive and poor households, increase the demand elasticity of firms. I next provide evidence consistent with this mechanism.

E. Composition effect versus levels effect

In principle, rainfall-induced demand shocks can have two opposing effect on prices. First, these shocks increase the aggregate demand for consumer products in the economy which can increase prices. By affecting the income of the poor population, deviations in rainfall changes the total demand and hence the market size. This is the *size effect*. Second, by affecting the market size of poor population relative to the wealthier population, these shocks change the composition of demand which could decrease prices. This is the *demand composition effect*. To separate out these effects, I start by decomposing the average price effects into a demand composition effect and size effect using the following specification:

$$\begin{aligned} \log y_{jpdt} &= \beta_1.\ [\text{Shock}_{dt} \times \mathbf{1}(\text{High share of rural population})_d] \\ &+ \beta_2.\ [\text{Shock}_{dt} \times \log(\text{Total Rural Population})_d] + \alpha_{jp} + \alpha_{pt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt} \end{aligned} \tag{13}$$

where y is either of price, markups or marginal costs. $\mathbf{1}(\text{Share of rural population})_d$ is a dummmy that takes the value of 1 for districts d with above median share of rural population. $(\text{Total rural population})_d$ is the rural population in the district. These demographic measures are from Population Census of 2001 to ensure that these variables do not endogenously respond to rain shocks in a particular year, for example due to migration responses to better opportunities in the agricultural sector. The size effect is estimated by β_2 which reflects the effect of local rain shocks across districts with larger or smaller rural population. The composition effect is estimated by β_1 which captures the effect of local rain shocks across districts depending on their share of rural population.

Table IX presents the results from specification 13. Column (1)-(3) shows the average demand effect from before. Column (4) shows that the negative demand effect of rain shocks is driven by districts with higher share of rural population. Consider two districts with same size of rural population. The estimates implies that districts with higher share of rural population decrease their prices by 1.8 percent compared to 1 percent in districts with lower share of rural population. Column (5) shows that the effects primarily by markups. Conditional on districts with equal size of rural population, districts with higher share of rural population decrease their markups by 3.5 percent. Finally, Column (6) shows that while marginal costs are significant in district with higher rural population, they are positive in magnitude.

F. Mechanism: Demand Composition Channel

Why would firms reduce their markups in response to rainfall-induced demand shocks? As per the demand composition channel (Prediction 3 in Section IV), an increase in the market size of the poor households relative to the wealthier households induces a change in the average demand elasticity faced by firms that cater to both rich and poor households. Under the purview of the assortative matching, this implies that demand composition, and hence markups, should change for firms in the middle of the size distribution. On the other hand, smallest and largest firms cater only to poor and rich consumer base, respectively, and thus rain shocks should not effect their demand composition. To test this prediction, I estimate the effect of rain shock on each quartile of firm-size distribution through the following equation:

$$\log y_{jpdt} = \sum_{r=1}^{4} \beta^r . \, (\text{Shock}_{dt} \times Q_i^r) + \alpha_{jp} + \alpha_{pt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt} \qquad (14)$$

where $r \in \{1,4\}$ indexes each of the four quartiles of the size distribution and Q_i^r are dummy variables taking the value of 1 when firm i belongs to quartile r.[26] I first analyse the effects of rain shocks on quantity sold across the firm size distribution. I then examine the effects of rain shocks on how firms across the size distribution change their markups and marginal costs.

Estimation results are presented in Table VIII. I first start by documenting that rain shocks have a monotonic effect on quantities of their product sold by the firms. Column (1) shows that in response to a positive rain shock the quantities sold by firm in the first and second lowest quartile of size distribution increase by 3 percent and 2.5 percent respectively. There is an increase in quantities sold (about 1 percent) for firm in the third quartile of the distribution but it is imprecisely estimated. Finally, there is no effect on the quantity sold by the firms in the top quartile of the distribution. Thus, rain shocks induced demand responses for firms that are decreasing across the firm size distribution. However, it could still be possible that different sized firms were growing at differential rates. In Column (2), I controls for such differential growth by including any the interaction of different size quartiles with year dummies. The estimates remain qualitatively unchanged. Next, I allow for rain shocks to have differential effect based on firms' age. As documented by Peters (2018), firms might adjust their markups and prices over their life cycle. As firm size and markups might be determined by such forces, I control for rain shock interaction with firm age in Column (3). The magnitude of the estimates is stable and robust to the inclusion of these controls.

However, in contrast to the effect on physical sales, we would not expect such monotonic relation with respect to markups. The markup charged by a firm inversely depend on its *sales-weighted* average price elasticity, where the weights are share of firm's sales made to each income group. Therefore, any change in relative demand from poor households changes the *sales-weighted* elasticity, and hence markups, only for firms that cater to both rich and poor households — proxied in the data by firms in the middle of the size distribution. To test this prediction, I estimate the effect of rain shock on each quartile

[26] I use initial firm size in terms of (log) employment relative to two-digit industry average in the district. I use 2-digit industries instead of products so as to increase the number of observations within each quartile and reduce the noise associated with misclassfication. I obtain similar results if I alternatively used (log) total sales as proxy for firm size.

of firm size distribution using the same specification 14 with (log) product markups as the dependent variable. Estimation results are presented in column (4)-(6) of Table VIII. Rain shocks only effect prices and markups in the middle of the productivity distribution. The estimated coefficient of -0.9 (*s.e.*=0.27) and -0.7 (*s.e.*=0.27) in the second and third quartile, respectively, of the size distribution is more than two to three times larger than the lowest quartile. Firms in the largest size quartile do not change their markups as well. The estimates remain stable if I allow for time-varying effects across size quartiles and after controlling for differential effect of rain shocks across firms' age. Finally, I examine the effect of rain shocks on the marginal costs across firm-size distribution. As column (7) to (9) show, while the effect of rain shock on marginal costs across the firm size distribution is positive, it is statistically insignificant.

The point estimates of β^r suggests that in years of positive rain shock induce firm in the second quartile of size distribution lowered their markups by 1 percent. The finding that firms in the lowest quartile of size distribution do not lower their markups is consistent with the hypothesis that the demand composition did not change for these firms significantly. Similarly, firms in the top quartile of the size distribution do not change their prices or markups as rain shocks have no effect on their demand. This is consistent with the finding that no changes to their sales keeps the demand composition unchanged for the largest firms.

Next, I test whether the demand composition effect is indeed higher in district with higher share of rural population. If rainfall driven demand shocks are indeed driving the observed markup responses, we should expect the non-monotonic markup responses of rain shocks across firm size distribution to be stronger in regions with higher share of rural population. To test for differential effect of rainfall across firm size distribution across districts with high versus low share of population employed in agriculture, I use the following specification:[27]

$$\begin{aligned}\log p_{jpdt} &= \sum_{r=1}^{4} \beta^r_{\text{above}} \cdot \left(\text{Shock}_{dt} \times Q^r_i \times \mathbf{1}[\text{Rural share} > \text{Median}]_d\right) \\ &+ \sum_{r=1}^{4} \beta^r_{\text{below}} \cdot \left(\text{Shock}_{dt} \times Q^r_i \times \mathbf{1}[\text{Rural share} <= \text{Median}]_d\right) \\ &+ \text{Shock}_{dt} \times \log(\text{Total Population})_d + \alpha_{jp} + \alpha_{pt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt}\end{aligned} \tag{15}$$

As before I always include the interaction of rain shocks with total population of the district which controls for the impact of rain shocks based on the size of the market. Column (5)-(6) of Table XII shows the negative responses of rain shocks for mid-sized firm is stronger in district with larger share of rural population. Taken together, these estimates reinforce the demand composition channel.

G. *Effects by product differentiation*

As documented in Section III, cross-sectional markup dispersion is higher for firms in sectors with greater scope for quality differentiation. Driven by lower demand elasticity of the rich, larger firms in these sectors are less exposed to competition and are able to charge higher markup. Therefore, one

[27] For brevity, I report the average effects when testing for composition effect versus level effect. The level effect is insignificant if I conduct the same exercise with interaction of these coefficient firm size quartiles.

would expect firms producing more differentiated goods to be more responsive to changes in demand composition. For example, lower competition would allow firms to increase their markups in response to negative demand shock due to their now lower demand elasticity. I test whether firms producing more differentiated goods change their markup more by estimating the following specification:

$$\begin{aligned}\log p_{jpdt} \quad = \quad & \sum_{r=1}^{4} \beta^{r}_{\text{above}}.\ (\text{Shock}_{dt} \times Q^{r}_{i} \times \mathbf{1}[\text{Z}_{j} > \text{Median}]) + \\ & \sum_{r=1}^{4} \beta^{r}_{\text{below}}.\ (\text{Shock}_{dt} \times Q^{r}_{i} \times \mathbf{1}[\text{Z}_{j} <= \text{Median}]) + \alpha_{jp} + \alpha_{pt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt} \qquad (16)\end{aligned}$$

where $\mathbf{1}[\text{Z}_j > \text{Median}]_d$ are dummy variables taking the value of 1 for firms in sector with greater scope for quality differentiation and 0 otherwise. Table XII reports the results. Column (1)-(2) of Table XII shows that markup responses to rain shocks across firm size distribution are stronger in sectors with greater scope of product differentiation. Taken together, these findings suggests that markups are more dispersed and respond more to demand shocks for firms less exposed to competitive pressure.

H. Effects across industries and products

If the rain shocks do indeed reflect changes in demand, we would expect to find a stronger effect in industries and products in which the local rural population represents a larger share of markets for firms. The results in the previous section document that rain shocks do not effect marginal costs and therefore any price responses are driven by changes to markups. In this section, I present additional evidence that show that the price effects are not driven by endogenous supply-side effects on markup. To begin with, Figure A.6 shows that the negative effect of rain shock on prices is driven by consumer good industries like clothing, furniture, paper products and processed food and beverages. These are the goods for which temporary shocks affect poor households demand. On the other hand, the price effects of rain shocks is negligible in heavy product industries such as medical equipment, chemical, transportation and minerals.

To formalize this argument, I estimate specification 16 based on tradability of the product. The idea is that local demand should have stronger effects among products that are less tradable, and the demand curve for more tradable goods should not shift in response to local income variations. To do so, I create industry level classification of tradability that relies on the fact that non-tradable goods production tend to be scattered across the country. A concentration index at NIC 3-digit is created using the number of labor employed in the sector. It is important to note that this definition is constructed using the 2005 Economic Census. Unlike ASI data, Economic Census surveys every non-farm establishment in the country and records the industry and number of employees. As an example, this classification assigns cement manufacturing sector as non-tradable whereas manufacturing of car parts on the other hand is classified as tradable.[28] The prices for non-tradable goods decrease by average of 0.6 percent percent. On the other hand, rain shocks have no effect on price of firms in tradable industries.[29] Column (3) and (4) of

[28] As cement converts to concrete soon after production, it consumer market tends to be very localized.

[29] I only report results for top and bottom quartile of the tradability classification. This is to reduce any noise in the middle of the distribution. If I consider the cutoff point to be the median of this distribution, results are much noisier.

Table XII shows that the non-monotonic effects of rain shocks across firm size distribution is stronger for firms in non-tradable industries. These results provide further evidence on the role of changing demand composition for markup cylicality.

I. Effects of positive versus negative shocks

An advantage of the setting is that it allows me to study the effect of both positive and negative shocks on markups. The demand composition channel posits a symmetric effect of positive and negative demand shocks on prices and markups. In Figure IX, I test whether the average relationship documented before holds separately for negative and positive shock. Panel (a) of the figure confirms that the non-monotonic effect of rain shocks on markups is present for both positive and negative rain shocks. Consistent with before, Panel (b) of the figure shows that marginal costs do not vary with either of positive and negative shocks. These findings are reassuring for two reasons.

J. Wholesalers versus Retailers: Evidence from Retail Store Prices

Results in previous section suggests that manufacturing firms in the middle of the size distribution lowered their prices and markups in response to positive rain shocks. The presence of stronger responses in non-tradable goods is consistent with the influence of demand factor driving these effects. In this section, I complement the existing analysis using retail-level data on the prices obtained across 168 product category by survey of shops in villages across 500 districts from 2001-2010.[30] This database allows me to study whether the price effects we observe at the manufacturer levels are indeed present in the final prices paid by the consumers. I conduct two analyses with the data. First, I verify if the average negative demand documented in the wholesale prices (ASI data) is also observed in the retail data. Second, the monthly frequency of the data allows me to separate whether prices respond to anticipation of the income shocks or post realization of income shocks.

Average effects on retail prices. Table X presents the effect of rain shocks on retail prices using the RPC data. In Panel (a), I conduct the analysis on store-product-month as my unit of observation using the following specification:

$$\log \text{price}_{psdm(t)} = \beta \ . \ \text{Shock}_{dt} + \mu_{ps} + \mu_{pm(t)} + u_{psdm(t)} \tag{17}$$

where p denotes product sold in shop s of district d in year t and month $m(t)$. Similar to the analysis on wholesale prices, I control for store-product fixed effects (μ_{ps}) to absorb permanent differences in quality or price levels across products in different store-districts and product-month fixed effects ($\mu_{pm(t)}$) to absorb macroeconomic shocks at the product level. Column (1) shows that retail prices decrease by 0.3 percent in years of positive rain shocks. While the effect is almost half of manufacturing prices (average

[30]The retail prices data also provide the prices on 82 foods item including cereals and pulses. I use information on prices of food item to validate the data: rain shocks, through their impact on agricultural productivity, are supply shocks to crops and I verify that the prices for cereals and pulses go down in responses to the positive agricultural productivity shocks and go up in response to negative shocks.

retail prices go down by 0.4 percent in response to positive rain shock), this can be attributed to the fact that retail prices do not cover product categories at a finer level as the ASI database. Column (2)-(5) breaks down the average effects by broad industry. While the negative effects are present in all of the industries, they are stronger in clothing and education supplies goods.[31] Panel (b) shows that the effects remain stable if I collapse the observations at district-product level instead.

Demand Composition channel in retail prices. Unlike wholesale data, I do not observe the firm identifier for the retail products and therefore I am not able to assign them into a particular size quartile. Instead, I rely on district-level analysis to provide evidence consistent with the demand composition channel. Specifically, as before, I decompose the average effect of rain shocks on retail prices into a composition effect and size effect based using specification 13. Table XI presents the results. Column (1) documents that the effect of rain shocks in retail prices is indeed decreasing in district with higher share of rural population. The estimates remain stable if I control for size effect, which is positive, in Column (2); or conduct the analysis instead using the average annual prices for the product in district (Column (3)-(4)).

Evidence from retail timing. An advantage of the RPC data is that it allows me to observe retail prices at monthly frequency. Observing price information at this frequency allows me to test when do prices change precisely over the agricultural cycle. 85% of agricultural production in India happens in the *kharif* season which begins in May of each year. The sowing period extends from May-September, with harvesting season extending between October and February. Farmers begin to realize the return on their farm investment starting with the harvesting period. This time variation within the agricultural year can be used to test whether the firms change their prices in response to "anticipated" demand shock in the near future or when consumer realize their income and uncertainty related to demand is resolved. To do so, I run the following specification to estimate monthly effects of rain shock on retail prices:

$$\log \text{price}_{pdm(t)} = \sum_{k=1}^{12} \left[\beta_k \, . \, \text{Shock}_{dt} \times (1_{m(t)} == k)\right] + \mu_{pd} + \mu_{pm(t)} + u_{pdm(t)}$$

Figure VIII shows that retail prices decrease right in the harvesting season when the uncertainty regarding their customer base is resolved. The results are consistent with the main results on wholesale prices and markups. As these retail prices are from villages shops, they would arguably correspond to the responses observed in the first two quintiles of the firm size distribution. These results altogether are suggestive that demand shocks to the poor lowers the average prices in the local economy.

Next, in Appendix C, I consider channels alternative to my mechanism, which might explain the heterogeneous price and markup responses across firm size distribution to demand shocks observed in the data. I consider four leading explanations in the existing literature that could generate countercyclical price and markup responses to demand shocks. First, in an economy with monopolistic or oligopolistic

[31] Few examples for products in clothing categories includes mill-cotton saree, khadi shirt cloth, mill-cotton dhoti, mill-bath towel, woollen scarf, ready-made cotton shirt, leather shoes etc. Examples for products in education category include text books, ball-point pen, lead pencil, exercise books, foolscap paper.

competition, markups countercyclicality could be an outcome of either procyclical business formation or new product innovation in response to an increase in market size. Second, firms might collude when setting their prices and the incentives to deviate from such collusive agreements could increase during periods of higher demand. Third, consumers might increase their search intensity in shopping during periods of peak demand, therefore increasing the price elasticity faced by firms. Fourth, accessing costly external in the presence of sticky consumer base could force financially constrained firms to increase markups during recessions. A common distinction between these channels and the demand composition channel proposed in this paper is that the prediction of non-monotonic markup responses to demand shocks across the firm size distribution is unique only to the latter. Nevertheless, I examine each of these explanations separately and find empirical evidence inconsistent with any of them driving my results.

Finally, I conduct a set of robustness checks. First, I first show that there is no selective rural migration in response to rain shocks. Second, firms are not changing their product quality, in response to changes in rural demand, that in turn could affect their prices and markups. Third, I show that my estimates are robust if I consider state to be the level of consumer market instead of districts. Fourth, the results are unchanged to using alternative definitions of rain shocks. Lastly, I show that there is no effect on quantity sold, prices and markups for exporters in my data set.

VII Implications

This paper has established that (i) consumer market segmentation generates systematic markup dispersion within narrow product categories (ii) increase in income for poor lowers price and markups for consumer goods due to changes in demand elasticities faced by firms. In light of these findings, I next discuss their implications for (a) policies aimed at reducing markup dispersion and (b) for social cash transfer programs targeted to the poor.

A. Dispersion in revenue-based productivity

When examined through the lens of a standard model of production and demand, dispersion in revenue total factor productivity (TFPR) suggests existence of distortions that prevent the efficient allocation of resources across firms in an industry (Hsieh and Klenow (2009)). Recently, a literature has deviated from the neoclassical view and has argued that systematic markup variation across firms is an underlying source of TFPR dispersion (De Loecker (2011); Peters (2018)). Existing literature has taken this markup dispersion solely driven by underlying misallocation. However, when markup dispersion is manifested through difference consumer elasticities faced by firms, then it need not be a source of misallocation.

To make this argument, I quantify the role of demand-driven markup variation for overall dispersion in TFPR. I calculate the fraction of TFPR dispersion that can be attributed to variation in markups across firms separately across homogeneous goods sectors and differentiated sector.

$$\text{TFPR} = \text{Price} \times \text{TFPQ} = (\text{Markup} \times \text{MC}) \times \text{TFPQ}$$

Taking logs and decomposing the variation in TFPR into its underlying components gives:

$$var(\text{tfpr}) = var(\mu) + var(s) + 2 \times cov(\mu, s)$$

where $s = \log(\text{MC} \times \text{TFPQ})$. The underlying markup variation is assumed to be coming from two sources: (i) a systematic source of underlying misallocation (Γ_i) (ii) demand-driven markup variation (ψ_i). The demand-driven markup variation is generated due to differences in the demand elasticities faced by firms and is independent of underlying misallocation: $\mu_{it} = \Gamma_{it} + \psi_{it} \quad (\Gamma_{it} \perp \psi_{it})$. The markup variation is:

$$\underbrace{var(\mu)}_{\substack{\text{total markup}\\ \text{dispersion}}} = \underbrace{var(\Gamma)}_{\substack{\text{common dispersion}\\ \text{across sectors}}} + \underbrace{var(\psi)}_{\substack{\text{dispersion due to}\\ \text{demand factors}}}$$

Table I below decomposes the share of TFPR dispersion coming from markup into a systematic channel (that drives common markup variation) and a demand-driven channel. It shows that 38 percent of the TFPR variation is driven by markups in the homogeneous goods sector, while this variation increases to 46 percent in the quality differentiated sector. Therefore, at least 8 percent of the variation in TFPR measure is driven by demand-driven markup variation. Misallocation losses are thus smaller by at least 8 percent because high productivity and larger firms who charge high markups do so precisely because they face low demand elasticities. This implies that a benevolent planner cannot achieve large gains by reallocating factors of production towards high productivity firms.

Table I: Fraction of variance in TFPR from markups $\left[\frac{var(\mu)}{var(\mathbf{tfpr})}\right]$:

Quality differentiation		
homogeneous	differentiated	difference
var(Γ_{it})	var$(\Gamma_{it}) + var(\psi_{it})$	var(ψ_{it})
+ 0.38	+ 0.46	+ 0.08

B. Implications for cash-transfer programs to the poor

Governments across the world have been implementing anti-poverty programs. Many developing countries have introduced public employment program, in which the poor receive minimum wage payment through guaranteed employment (e.g., National Rural Employment Guarantee Act (NREGA) in India). In the US, transfer policies targeting the poor range from food stamps, the EITC, UI and DI insurance, the minimum wage, Social Security transfers, the possible introduction of a universal basic income. These policies will all affect the relative market size of different groups of agents, and change the demand composition for firms, with price effects that will determine the equilibrium *real* effects of the policy change. The estimated elasticity of prices to rural income in the paper can be used to inform on the equilibrium effects of such policies. The results documented in the Section VI showed that a 1 percent increase in income of the poor lowers the prices for consumer goods in the local economy by 0.15 percent. Therefore, under these price effects, policies aimed at transferring cash to the poor can generate a *multiplier effect*.

To see this, let Y be the income for the poor households, P be the aggregate price index faced by them and Q be their aggregate real consumption. Under no savings, $Y = P \times Q$. Consider a benevolent planner that decides to transfer cash worth $d\log Y$ percent of the income of poor household. Under no effect of income on prices, $d\log Y = d\log Q$ and transferring 1 percent additional cash to the poor implies a 1 percent increase in their real consumption. However, under the elasticity of -0.15 of prices to income (of the poor), transferring 1 percent additional cash to the poor would increase the real consumption of the poor by 1.15 percent.[32] This multiplier effect is induced due to the demand composition channel and reduces the real consumption inequality between the poor and wealthier consumers.

VIII Concluding Remarks

This paper documents how demand-side characteristics affect the equilibrium distribution of markups across firms. The key mechanism is the assortative matching between consumers and firms on product quality: wealthier households source more of their consumption from goods produced by larger firms. Heterogeneity in consumer demand elasticities across income distribution translates into heterogeneity in markups charged by firms: lower demand elasticity of wealthier households allows larger firms to charge higher markups. Consistent with the predictions of a model that features two-sided heterogeneity in consumption and production, I provide empirical evidence consistent with the demand-based markup channel. The unique prediction of the model is the demand composition effect: in response to increase in relative demand from poor, quantities sold by firms follow a monotonic relation across the firm-size distribution, while the markup responses follow a non-monotonic pattern. Specifically, in response to positive income shocks to poor households, markups decrease only for mid-sized firms. They do not change for firms in either the lower- or upper-end of size distribution. I find strong empirical support for each of these predictions across firms in the Indian manufacturing sector.

The findings of this paper have several implications. First and most directly, they suggest that the dispersion in markups accounts for substantial variation in within-industry dispersion in TFPR documented in the existing literature. A literal implication is that when the markup dispersion is driven by efficient sources, such as demand factors documented in this paper, the welfare gains from policies inducing reallocation of factors of production are likely to be lower than otherwise implied under a standard model of production and demand. More broadly, the results reinforce the recent consensus in the literature that TFPR is not just technological in nature and that more analysis is required to further quantify the sources driving TFPR dispersion. For example, the finding that higher physical productivity is associated with higher marginal costs provides an additional channel of dispersion in TFPR measure that is reflective of differences in prices of input factors rather than misallocation. Identifying the role of such sources is

[32] To see this, notice that under price effects $d\log Y = d\log P + d\log Q^*$. Under price effects, $\frac{d\log P}{d\log Y} = -0.15$, which gives us the following multiplier effect: $d\log Q^* = 1.15 \times d\log Y = 1.15 \times d\log Q$.

important in quantifying the aggregate productivity gains achievable through resource reallocation.

Second, the results from the empirical strategy incorporated in the paper speaks to the vast literature in macroeconomics on markup cyclicality across demand-driven business cycles. The findings suggest a new source of markup cyclicality: procyclical *firm-level* demand elasticity. Income shocks to poor increases the average demand elasticity faced by firms by changing their demand composition. In response, firms optimally lower their prices and markups. Therefore, even though this paper focuses on India — a middle-income country — due to availability of high-quality data on manufacturing firms and appealing empirical setting, the mechanism identified in the paper is general and will apply to other settings as long as recessions are accompanied by decrease in expenditure share from more demand elastic consumers.

Finally, the findings of this paper have direct implications in explaining sensitivity of small firms over business cycles. A large literature in macroeconomics and corporate finance has documented that small firms in the US are more responsive to aggregate shocks. Following the work of Gertler and Gilchrist (1994), literature has paid close attention to financial frictions faced by firms as primary driver in explaining the excess sensitivity of small firms. The common idea behind these papers is that smaller firms are more financially constrained than larger firms that have easier access to financial markets or have more tangible assets to pledge as collateral. The unavailability of affordable financing during economic downturns affects smaller firms relatively more than larger firms. My empirical evidence suggests an alternative role for demand shocks as potential driver of excess sensitivity of smaller firms. Excess income sensitivity of poor consumers to aggregate shocks — as documented in Guvenen et al. (2017) — combined with their higher marginal propensity to consume, could translate to excess demand sensitivity for small firms.[33] I relegate understanding these implications for future research.

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[33] In recent work, Crouzet and Mehrotra (2019) provide evidence on excess sensitivity of small firms to business cycle fluctuations in the US. While the authors find that sales, inventory and investment of small firms are more responsive to aggregate shocks, they rule out financial frictions as potential underlying explanation for these responses. They provide suggestive evidence attributing the lower sensitivity of large firms to their diversified consumer base as proxied by export exposure and downstream diversification for the firm's industry.

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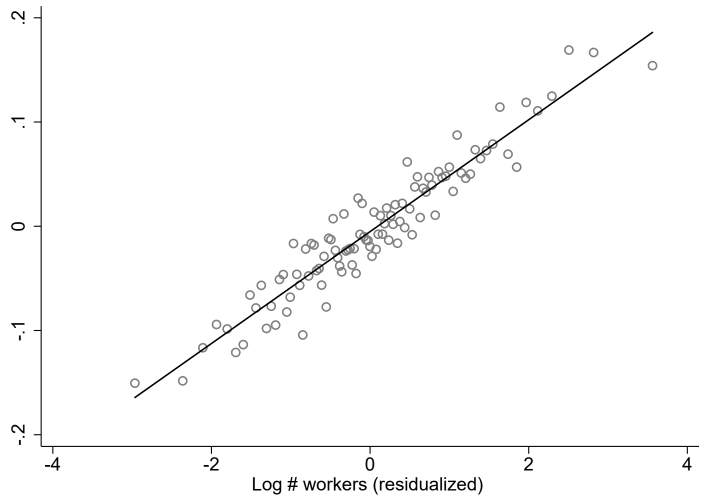
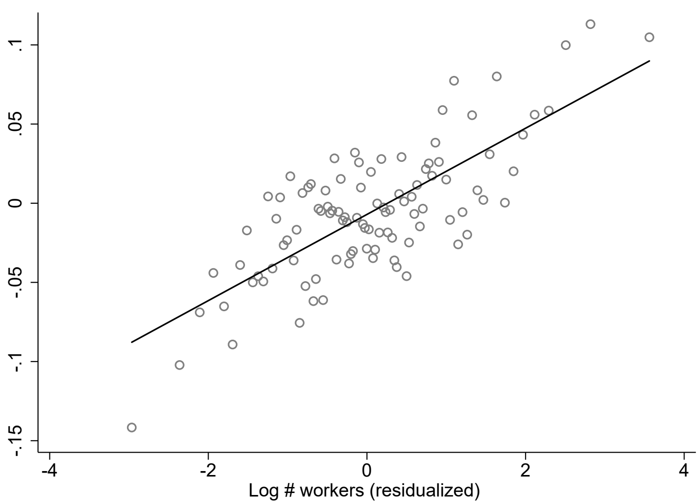
Figure I: Relation between firm's unit-level prices and size

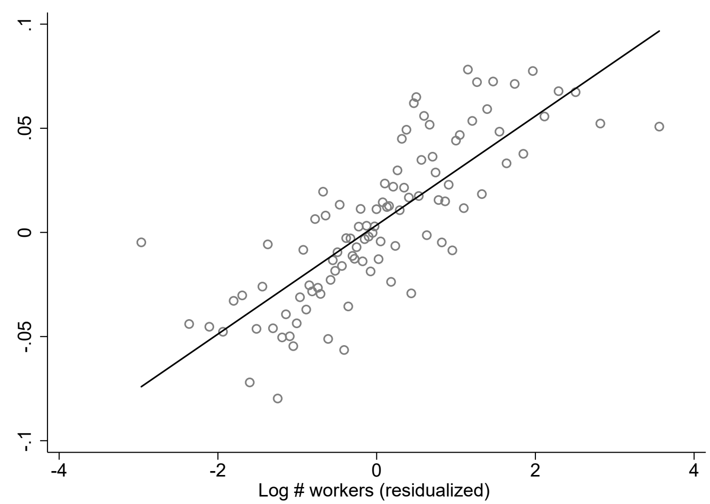
(a) log prices (residualized)



(b) log marginal costs (residualized)

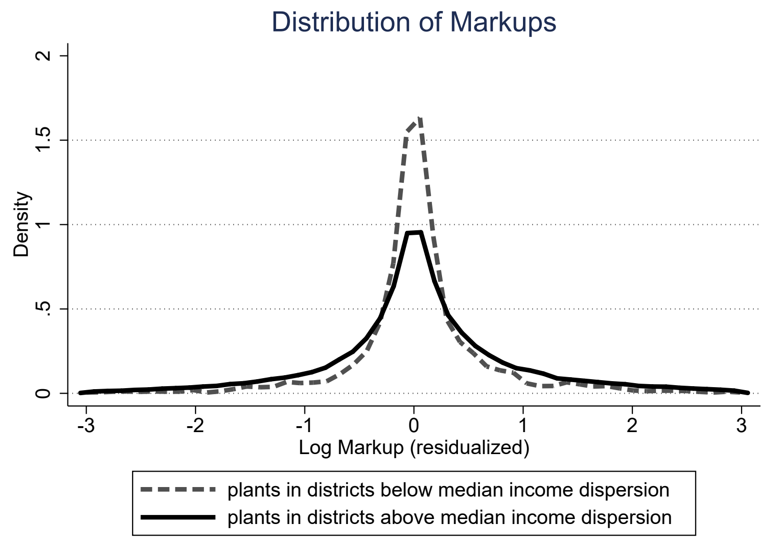


(c) log markups (residualized)



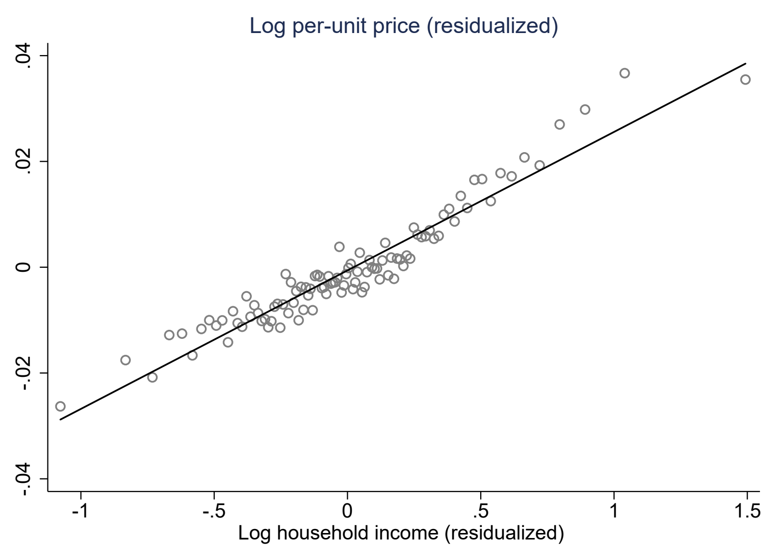
Notes: The top-panel shows the relation between firm's per-unit product prices and size (as measured by its labor force). The *y*-axis depicts the residuals of a regression of firm's log per-unit prices on district-by-product-by-year fixed effects. The *x*-axis depicts the residuals of a regression of firm's log number of workers on district-by-industry-by-year fixed effects. Each dot represents 1% of observations. Source: ASI

Figure II: Markups kernel density estimates, plants in markets above and below median income dispersion



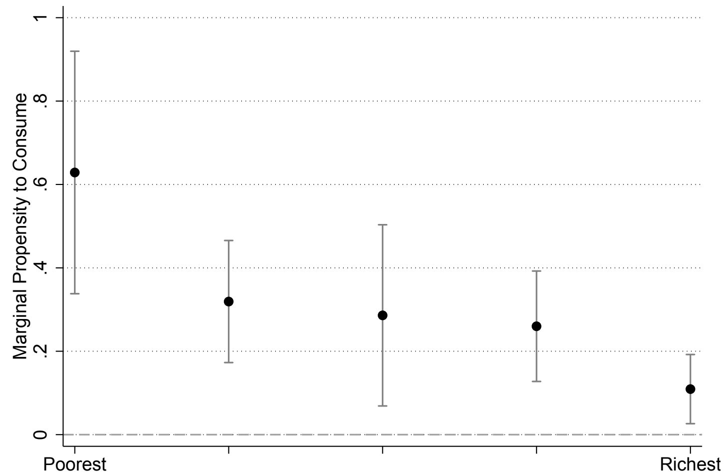
Notes: The figure shows the distribution of residualized log markups across firms in Indian districts below and above the median income dispersion. The *x*-axis depicts the residuals of a regression of firm's log per-unit markups on district-by-product-by-year fixed effects. Income dispersion for a district is defined as the standard deviation in household income in National Sample Survey (NSS) data for that district in the year 2002. Plant-level information is sourced from Annual Survey of Industries (ASI) data.

Figure III: Household income and per-unit product prices



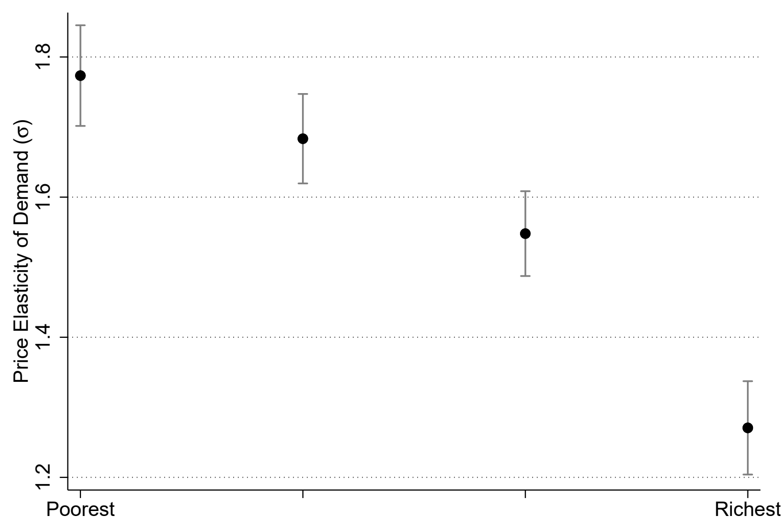
Notes: The figure shows the relation between average log unit-value deviations for manufactured goods and household average consumption. The *y*-axis depicts the residuals of a regression of log unit-level price on product-by-village-by-year fixed effects. The *x*-axis depicts the residuals of a regression of log household consumption (as proxy for income) on product-by-village-by-year fixed effects and household controls (including industry of occupation, type of occupation, religion and social group). Each dot represents 1% of observations. Source: NSS

Figure IV: Marginal Propensity to Consume (MPC) across income groups



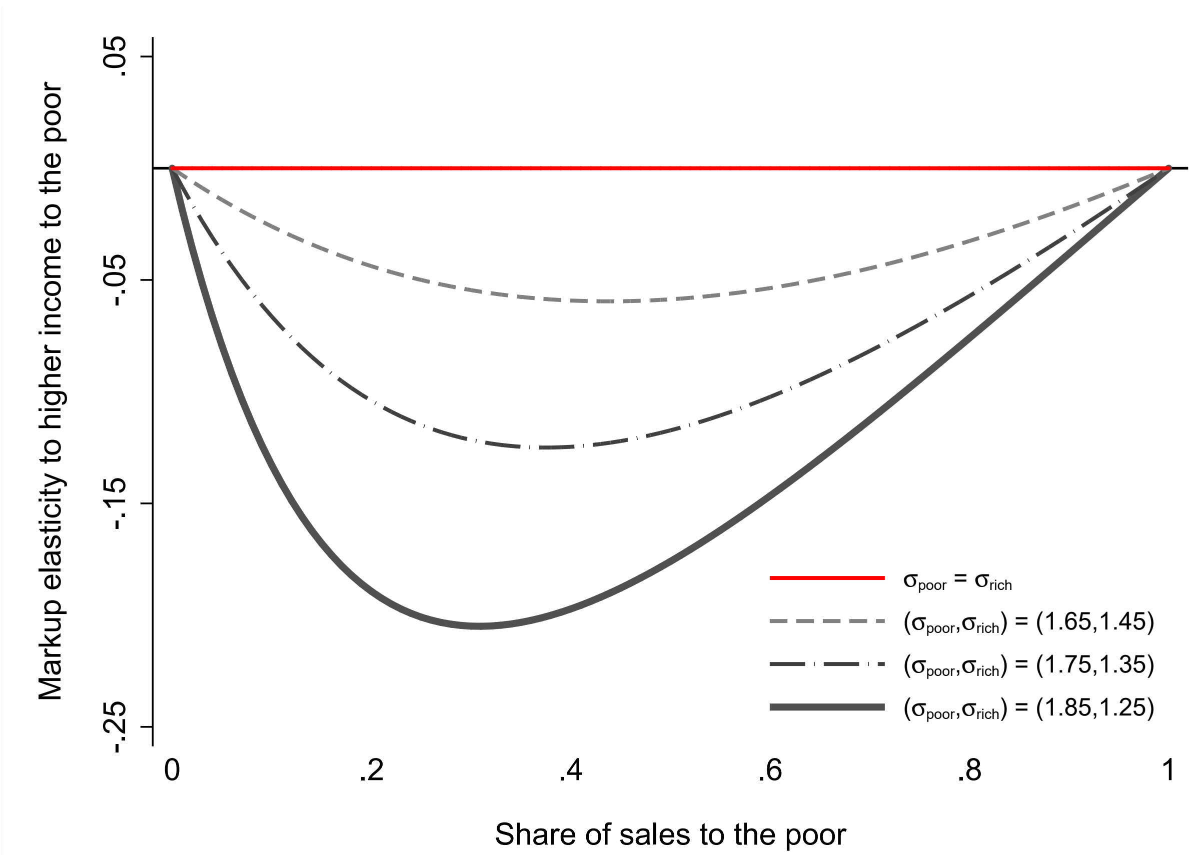
Notes: The figure reports the estimate of marginal propensity to consume (MPC) across income groups and uses changes in employment status as an instrument to changes in income. It plots the estimates $\alpha(z)$ across five income groups based on the following specification: $\Delta \log x_{ivt}(z) = \alpha(z)\ \Delta \log y_{ivt}(z) + \beta_i + \gamma_{vt} + \varepsilon_{ivt}$ where β_i is the household fixed effect and γ_{vt} is a region-year fixed effect that captures the total resources available in the region-month and aggregate shocks in month t. Source: CMIE

Figure V: Estimates of price-elasticity of demand (σ) by income groups



Notes: The figure reports the estimate of price-elasticity ($\sigma(z)$) of demand based on the estimating equation : $\Delta \log(x_{ir}(z)) = \alpha_{ir} + \alpha_z + (1-\sigma(z))\Delta \log(p_{ir}) + \nu$, where i is a product variety, h is a household in region r surveyed in year t. $x_{ir(z)}$ is the total amount spent by an household in income group z on product variety i and p_{ir} is the price of the variety. The estimates are based on a IV-2SLS specification that instruments Δp with state-level leave out mean price changes : $\frac{1}{N-1}\sum_{r' \neq r} \Delta log(p_{ri})$. Source: NSS

Figure VI: Elasticity of markups to positive income shocks to poor (as function of share of sales made to the poor by firm)



Notes: The figure shows simulated relationship of how markups should respond to positive income shocks to households that are more price-sensitive households, based on equation 9 in Section IV. It plots the relationship as a function of share of sales made to the poor households (i.e. households with higher demand elasticity) by the firm.

Figure VII: Geographical distribution of rainfall shocks across India (1998-2009)

(a) Positive rain shocks (above 80^{th} percentile)

(b) Negative rain shocks (below 20^{th} percentile)

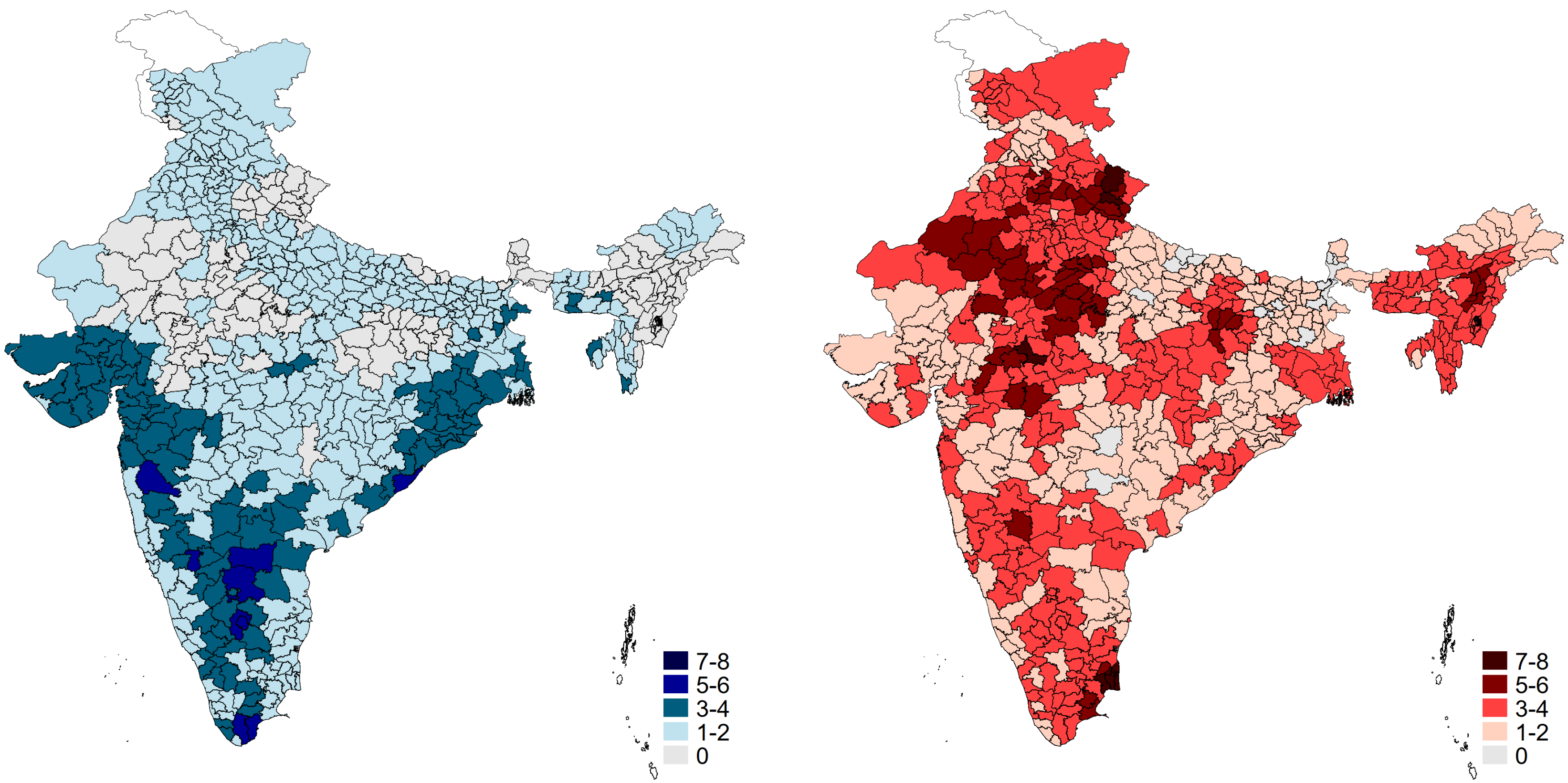
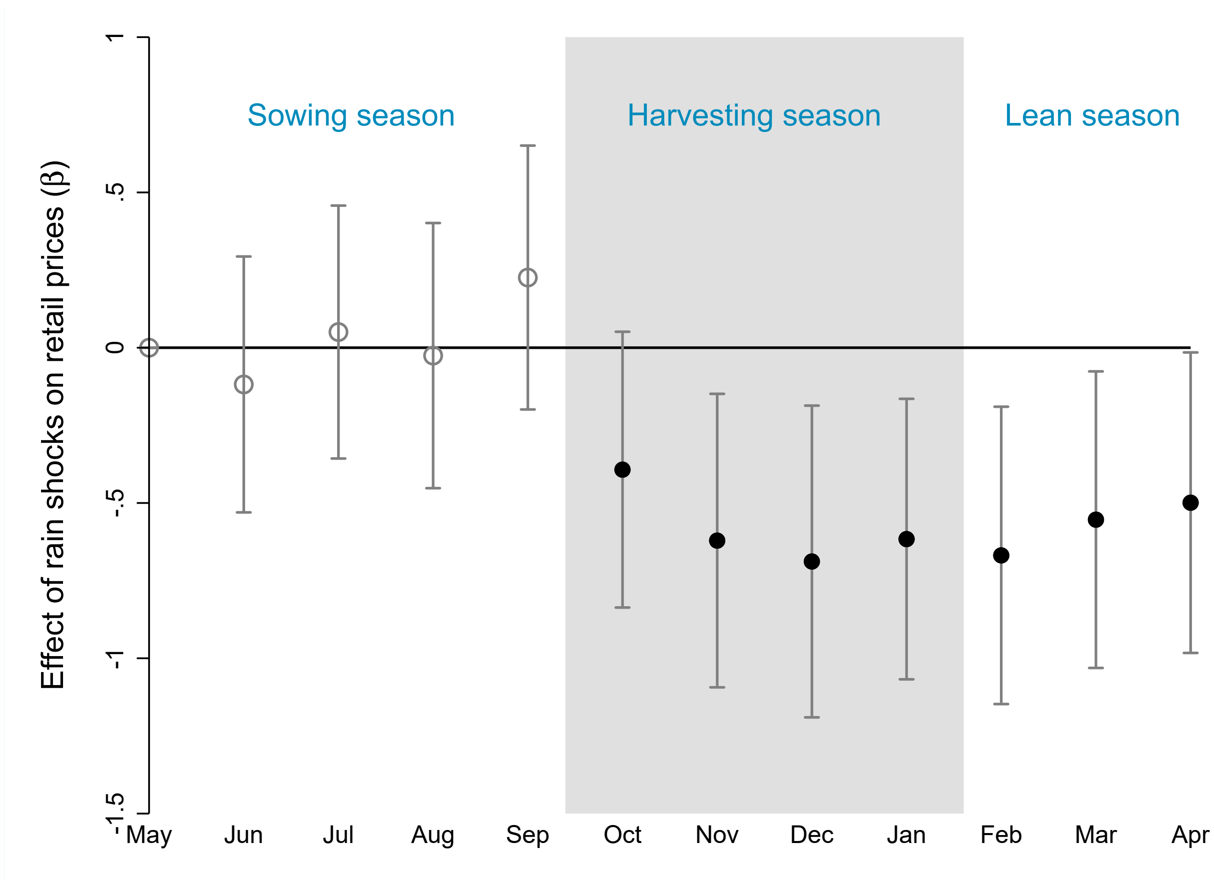


Figure VIII: Change in retail prices based on timing of the shock



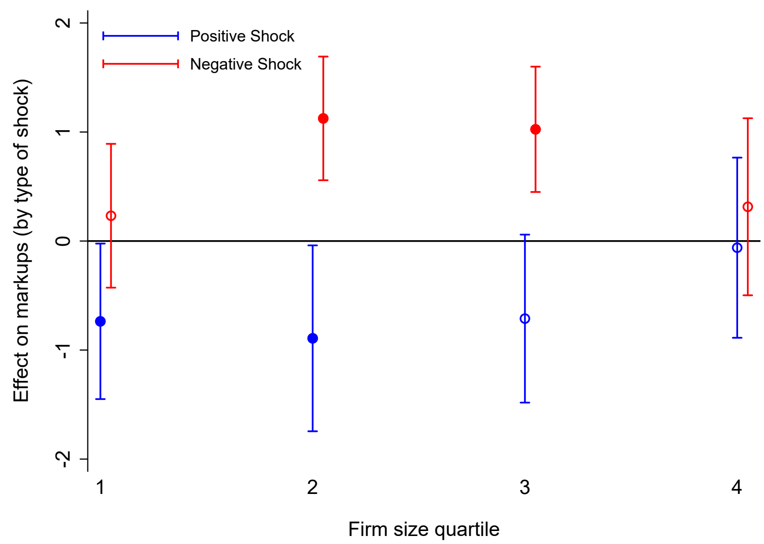
Notes: This plot test the response of retail prices based on the timing of agricultural cycle between the month on May in one year and the month of April in the next year and plot the coefficient β_k (multiplied by 100) from the following specification:

$$\ln \mathrm{p}_{pdm(y)} = \mu_{pd} + \mu_{pm(y)} + \sum_{k=1}^{12} \left[\beta_k \mathrm{Shock}_{dy} \times (1_{m(y)} == k) \right] + u_{pdm(y)}$$

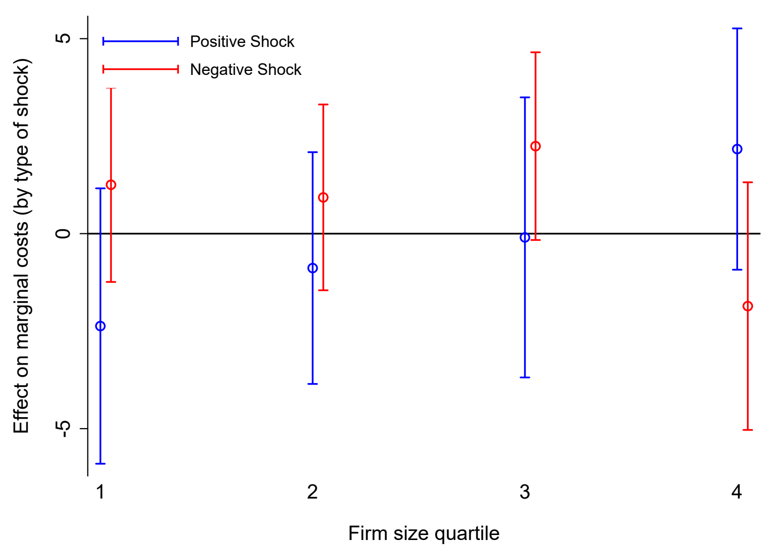
95% confidence intervals are represented in dashed red lines on the graph. Black circles indicate results that are significant at the 10% level, and hollow circles statistically insignificant from 0.

Figure IX: Effect on markups and marginal costs (by positive and negative shocks)

(a) Effect on markups



(b) Effect on marginal costs



Notes: The figure reports the heterogeneous effects of both positive and negative rainfall-shocks on markups (top panel) and marginal costs (bottom panel), based on specification:

$$\log y_{jpdt} = \alpha_{jp} + \alpha_{pt} + \sum_{r=1}^{4} \beta^{r,+}.\,(\text{Shock}^{+}_{dt} \times Q^{r}_{i}) + \sum_{r=1}^{4} \beta^{r,-}.\,(\text{Shock}^{-}_{dt} \times Q^{r}_{i}) + \Gamma' X_{jpdt} + \varepsilon_{jpdt}$$

where y_{jpdt} is the markup or marginal costs for product p produced by firm j in district d in year t. Shock^{+}_{dt} and Shock^{-}_{dt} takes the value of 1 if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. Q^{r}_{i} are dummy variables taking the value of 1 when firm i belongs to size quartile r within the industry k.

Table II: Baseline Correlations: Firm size and prices

	Dependent variable:					
	log (output product prices)			log (factor input prices)		
	Price	Marg. Cost	Markup	Material Inputs	K/L	Wages
	(1)	(2)	(3)	(4)	(5)	(6)
(log) labor	0.096***	0.041***	0.056***	0.063***	0.098***	0.189***
	[0.005]	[0.006]	[0.004]	[0.010]	[0.007]	[0.003]
Observations	167,221	167,221	167,221	443,022	167,221	167,221
R-squared	0.921	0.870	0.638	0.410	0.656	0.803
Industry f.e.	✓	✓	✓	✓	✓	✓
District-prod.-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table reports the correlation between firm j size (proxied by (log) labor) and (log) price, (log) marginal costs and (log) markups for their products, indexed by p, among manufacturing plants in India in the Annual Survey of Industries (ASI) data. It is based on the following specification:

$$\log y_{jpt} = \alpha_{kt} + \alpha_{dpt} + \beta \ \ \log(\text{labor})_{jt} + u_{jpt}$$

Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table III: Baseline Correlations: Firm size and prices across sectors

Dependent variable:	Markup	Marginal Cost	Material Inputs	K/L	Wages
	(1)	(2)	(3)	(4)	(5)
(log) labor	0.077***	-0.023***	0.051***	0.073***	0.184***
	[0.003]	[0.008]	[0.007]	[0.010]	[0.004]
(log) labor × different. good	0.009**	0.117***	0.019**	0.046***	0.008**
	[0.004]	[0.011]	[0.008]	[0.010]	[0.004]
Observations	167,221	167,221	443,022	167,221	167,221
Industry f.e.	✓	✓	✓	✓	✓
District-prod.-year f.e.	✓	✓	✓	✓	✓

Notes: The table reports the correlation between firm j size (proxied by (log) labor) and (log) markups , (log) marginal costs, for their products (indexed by p); as well as between firm size and factor prices (input prices, capital intensity and wages per unit labor), based on the scope of product differentiation among manufacturing plants in India in the Annual Survey of Industries (ASI) data. It is based on the following specification:

$$\log y_{jpt} = \alpha_{kt} + \alpha_{dpt} + \beta \left[\log(labor)_{jt} \times 1(\text{different. good})_p\right] + u_{jpt}$$

where 1(different. good) is a dummy taking the value of 1 if a product is classified as differentiated based on Rauch (1999) definition for product differentiation. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table IV: Rainfall induced income shocks for poor population

Dependent variable:	Agricultural output		Daily wages			Unemployment Rate	
	Crop yield	Revenue per unit area	Farmers	Agri. labor	Non-agri. labor	Farmers	Agri. labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock$_{dt}$ (-1/0/+1)	0.048***	0.036***	0.024**	0.040***	0.002	-0.003***	-0.006**
	(0.006)	(0.006)	(0.011)	(0.011)	(0.009)	(0.001)	(0.002)
Observations	38,280	38,280	52,019	39,875	126,962	152,900	61,548
District-crop f.e.	✓	✓					
Crop-year f.e.	✓	✓					
District f.e.			✓	✓	✓	✓	✓
Year f.e.			✓	✓	✓	✓	✓

Notes: The table reports the effect of rainfall shocks on agricultural productivity (Column (1)-(2)) and rural labor market (Column (3)-(7)). Shock$_{dt}$ is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table V: Average effect of rain shocks to poor on plant-level prices

	Dependent variable:			
	$\log q$	$\log price$		
	1^{st} stage	OLS	IV-2SLS	RF
	(1)	(2)	(3)	(4)
Shock_{dt}(-1/0/+1)	0.012**	-	-	-0.005***
	[0.005]	-	-	[0.002]
$\log q$	-	-0.062***	-0.392**	-
	-	[0.005]	[0.190]	-
Observations	133,094	133,094	133,094	133,094
F-stat	16.684			
Marginal Costs	✓	✓	✓	✓
Firm-product f.e.	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓

Notes: The table reports the average effects of rainfall-shocks on firm-level product prices, based on specification:

$$\log p_{jpdt} = \alpha_{jp} + \alpha_{pt} + \beta \times \text{Shock}_{dt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt}$$

where $\log p_{jpdt}$ is the log price of the product p produced by firm j in district d in year t. Shock_{dt} is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. All columns (but Column (1)) include firm-product and product-year fixed effects. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table VI: Robustness Checks: Average effect of rain shocks to poor on plant-level prices

	Dependent variable: log price × 100						
	Baseline Specification	Firm cost Controls	Single-plant establishment	National Market access control	In + out-state market access	Past 2-year shocks controls	(2)+(5)+(6) controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock_{dt} (-1/0/+1)	-0.441**	-0.464**	-0.488***	-0.512**	-0.466**	-0.485**	-0.466*
	[0.190]	[0.192]	[0.160]	[0.213]	[0.230]	[0.201]	[0.238]
Observations	133,094	130,310	122,828	133,094	133,094	133,094	130,310
Firm-product f.e.	✓	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓	✓

Notes: The table reports the average effects of rainfall-shocks on firm-level product prices, based on specification:

$$\log p_{jpdt} = \alpha_{jp} + \alpha_{pt} + \beta \times \text{Shock}_{dt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt}$$

where $\log p_{jpdt}$ is the log price of the product p produced by firm j in district d in year t. Shock_{dt} is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. All columns include firm-product and product-year fixed effects. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table VII: Average effect of rain shocks on firm markups and marginal costs

	Dependent variable:								
	Price	Markup	MC	Price	Markup	MC	Price	Markup	MC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shock_{dt} (-1/0/+1)	-0.441**	-1.144*	0.700	-0.464**	-1.237*	0.771	-0.485**	-1.102	0.615
	[0.190]	[0.664]	[0.749]	[0.192]	[0.665]	[0.745]	[0.201]	[0.691]	[0.770]
Observations	133,094	133,094	133,094	130,310	130,310	130,310	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	Baseline specification			Firm cost controls			Past 2-year shocks controls		

Notes: The table reports the average effects of rainfall-shocks on firm-level product prices, based on specification:

$$\log y_{jpdt} = \alpha_{jp} + \alpha_{pt} + \beta \times \text{Shock}_{dt} + \Gamma' X_{jpdt} + \varepsilon_{jpdt}$$

where y_{jpdt} is product p's price, markups, marginal costs produced by firm j in district d in year t. Shock_{dt} is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Columns (1)-(3) use the baseline specification that includes firm-product and product-year fixed effects. Columns (4)-(6) also control for firms cost controls including cost-to-assets and inventories-to-assets. Columns (7)-(9) include past two years' shocks as controls. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table VIII: Effects of rain shocks across firm-size distribution

	Dependent variable:								
	log (quantity sold) × 100			log (markup) × 100			log (marginal cost) × 100		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shock$_{dt}$ (-1/0/+1)									
× First size quartile	2.717***	2.203**	2.634**	-0.328	-0.358	-0.434	-0.465	-0.800	-0.828
	[0.955]	[1.018]	[1.045]	[0.312]	[0.285]	[0.309]	[1.298]	[1.323]	[1.403]
× Second size quartile	2.398***	2.435***	2.758***	-0.906***	-0.879***	-0.966***	-0.018	1.078	1.045
	[0.837]	[0.901]	[0.964]	[0.272]	[0.295]	[0.324]	[1.115]	[1.160]	[1.365]
× Third size quartile	0.734	1.053	1.412	-0.705**	-0.725**	-0.840**	0.464	0.817	0.774
	[0.761]	[0.822]	[0.914]	[0.278]	[0.283]	[0.358]	[1.321]	[1.419]	[1.740]
× Fourth size quartile	-0.093	0.018	0.805	0.128	0.148	0.009	2.842**	1.829	1.768
	[0.937]	[1.045]	[1.129]	[0.346]	[0.413]	[0.438]	[1.329]	[1.517]	[1.795]
Observations	133,094	133,094	133,094	133,094	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specification	Baseline	+ Size Quartile × 1(year)	+ Age × Rain shock	Baseline	+ Size Quartile × 1(year)	+ Age × Rain shock	Baseline	+ Size Quartile × 1(year)	+ Age × Rain shock

Notes: The table reports the heterogeneous effects (β^r) of rainfall-shocks on firm-product level quantity sold, its markups and marginal costs based on specification:

$$\log y_{jpdt} = \alpha_{jp} + \alpha_{pt} + \sum_{r=1}^{4} \beta^r . (\text{Shock}_{dt} \times Q_i^r) + \Gamma' X_{jpdt} + \varepsilon_{jpdt}$$

where y_{jpdt} is the outcome of interest for product p produced by firm j in district d in year t. Shock$_{dt}$ is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Q_i^r are dummy variables taking the value of 1 when firm i belongs to size quartile r within the industry k. All columns include firm-product and product-year fixed effects. Column (1),(4),(7) use the baseline controls only. Column (2),(5),(8) also include controls for size-quartile interacted with time dummies. Column (3),(6),(9) also include controls for firm age interacted with rainshock. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table IX: Composition effect versus size effect (ASI data)

	Dependent variable:					
	log (price)		log (markup)		log (marg. cost)	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock_{dt} (-1/0/+1)	-0.441**	-1.051**	-1.144*	0.533	0.700	-1.585
	[0.190]	[0.513]	[0.664]	[3.428]	[0.749]	[1.606]
Shock_{dt} $\times$ 1(High Share of rural pop.)$_d$	-	-0.788**	-	-3.412**	-	2.628*
	-	[0.379]	-	[1.379]	-	[1.379]
Shock_{dt} $\times$ log(Total rural population)$_d$	-	0.056	-	-0.072	-	0.128
	-	[0.036]	-	[0.244]	-	[0.123]
Observations	133,094	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table reports the effect of rainfall shocks on prices, markups (μ) and marginal costs (*mc*) and decomposes the average effect into a *composition* and *size* effects. Odd columns reports the average demand effects. Even columns reports the composition and size effects. Composition effect is the coefficient on [Shock_{dt} $\times$ (Share of rural population)$_d$], where share of agricultural population is defined as percentage of individuals involved in agricultural activites (farmers + laborers) in the district based on 2001 census. Size effect is the coefficient on [Shock_{dt} $\times$ (Total population)$_d$], where total population is sourced from the 2001 Census of India. All estimates are multiplied by 100 for improved readability. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table X: Average effect of rain shocks on retail store prices (RPC data)

	Dependent variable:				
	log (retail price) × 100				
	All	Clothing	Education	Personal Care	Durables
	(1)	(2)	(3)	(4)	(5)
	Observations at **store-product-month**				
Rain shock this year	-0.274***	-0.315***	-0.890***	0.090	-0.152***
	[0.023]	[0.032]	[0.071]	[0.059]	[0.052]
Observations	1,903,100	976,924	206,031	327,964	392,181
Number of products	84	47	8	13	16
Store-product f.e.	✓	✓	✓	✓	✓
Product-month f.e.	✓	✓	✓	✓	✓
	Observations at **district-product-year**				
Rain shock this year	-0.271***	-0.350***	-0.638***	-0.053	-0.053
	[0.067]	[0.091]	[0.205]	[0.156]	[0.158]
Observations	184,121	97,716	19,160	30,571	36,674
Number of products	84	47	8	13	16
District-product f.e.	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓

Notes: The dependent variable is the log of the nominal price for product c produced by firm i located in district d in year t. Observations are from the Retail price data from 1998-2009 averages over the year for every district-product type. Shock$_{dt}$ is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Column 2 and 4 reports the coefficient of rainfall shock after interact with broad product categories. Column 1 and 2 include district-product fixed effects and year-fixed effect and Column 3-4 include district-product and product-year fixed effects. Standard errors are clustered by district level are reported in parentheses.Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table XI: Composition effect versus size effect (Retail price data)

	Dependent variable:			
	log (price) $\times$ 100			
Level of observation:	Store-product-month		District-product-year	
	(1)	(2)	(3)	(4)
Shock$_{dt}$ (-1/0/+1)	0.435***	-1.121***	0.422	-0.990
	[0.102]	[0.274]	[0.299]	[0.780]
Shock$_{dt}$ $\times$ (Share of rural population)$_d$	-0.947***	-1.242***	-0.922**	-1.195***
	[0.133]	[0.141]	[0.387]	[0.411]
Shock$_{dt}$ $\times$ log(Total rural population)$_d$	-	0.125***	-	0.114*
	-	[0.020]	-	[0.058]
Observations	1,825,858	1,825,858	178,421	178,421
Fixed effects	Store-product + Product-month		District-product + Product-year	

Notes: The table reports the effect of rainfall shocks on prices retail prices and decomposes the average effect into a *composition* and *size* effects. Interpretability follows from Table IX All estimates are multiplied by 100 for improved readability. Robust standard errors are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table XII: Heterogeneous price-effects of rain shocks

	Dependent variable: log (markup) × 100					
	Product differentiation		Tradability		Share of population in agriculture	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Shock_{dt} (-1/0/+1)						
× First size quartile	-0.477	-0.327	-0.301	0.189	-0.377	-0.147
	[0.383]	[0.427]	[0.415]	[0.656]	[0.421]	[0.382]
× Second size quartile	-0.980***	-0.283	-1.114**	-0.227	-0.884**	-0.389
	[0.323]	[0.423]	[0.500]	[0.492]	[0.412]	[0.349]
× Third size quartile	-0.741*	-0.435	-0.917*	-0.304	-0.851**	-0.326
	[0.396]	[0.339]	[0.538]	[0.568]	[0.388]	[0.374]
× Fourth size quartile	0.032	0.165	0.129	0.122	-0.692	0.441
	[0.515]	[0.408]	[0.665]	[0.710]	[0.529]	[0.465]
Observations	111,453	111,453	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table reports the heterogeneous effects (β^r_{above} and β^r_{below}) of rainfall-shocks on firm-level product prices, based on specification:

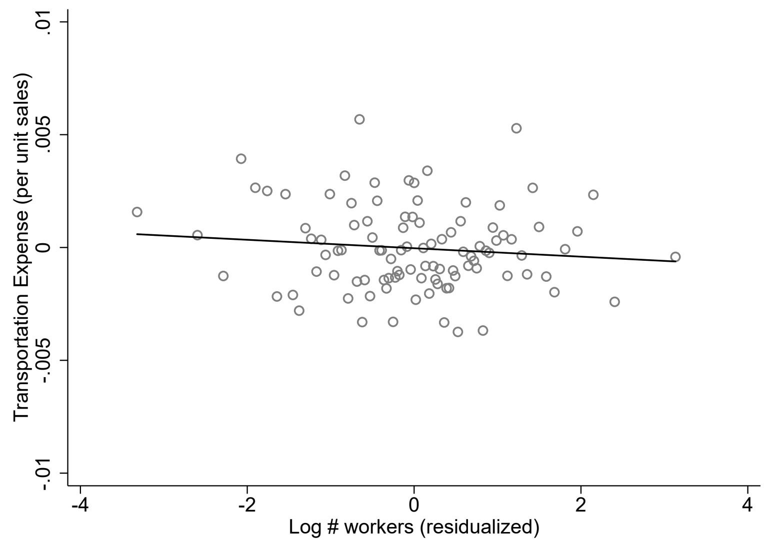
$$\begin{aligned}\log p_{jpdt} &= \alpha_{jp} + \alpha_{pt} + \sum_{r=1}^{4} \beta^r_{\text{above}} \cdot (\text{Shock}_{dt} \times Q^r_i \times \mathbf{1}[\text{Z}_j > \text{Median}]) \\ &+ \sum_{r=1}^{4} \beta^r_{\text{below}} \cdot (\text{Shock}_{dt} \times Q^r_i \times \mathbf{1}[\text{Z}_j <= \text{Median}]) + \Gamma' X_{jpdt} + \varepsilon_{jpdt}\end{aligned}$$

where p_{jpdt} is the per-unit price for product p produced by firm j in district d in year t. Shock_{dt} is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Q^r_i are dummy variables taking the value of 1 when firm i belongs to size quartile r within the industry k. Z is a classification that represents Rauch (1999) product differentiation in Column (1)-(2); product tradability in Column (3)-(4); and a districts' share of agricultural population in Column (5)-(6). $\mathbf{1}[\text{Z}_j > \text{Median}]_d$ are dummy variables taking the value of 1 if firm-product ij is above median in the classification and zero otherwise. All columns include firm-product and product-year fixed effects. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix for "Firm Heterogeneity, Demand For Quality and Prices: Evidence from India"

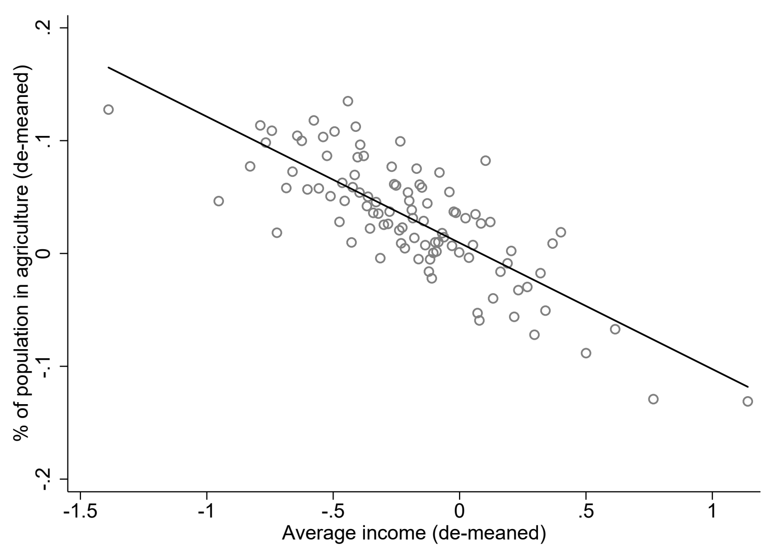
A Appendix Figures and Tables

Figure A.1: Relation between transportation expenses and firm size



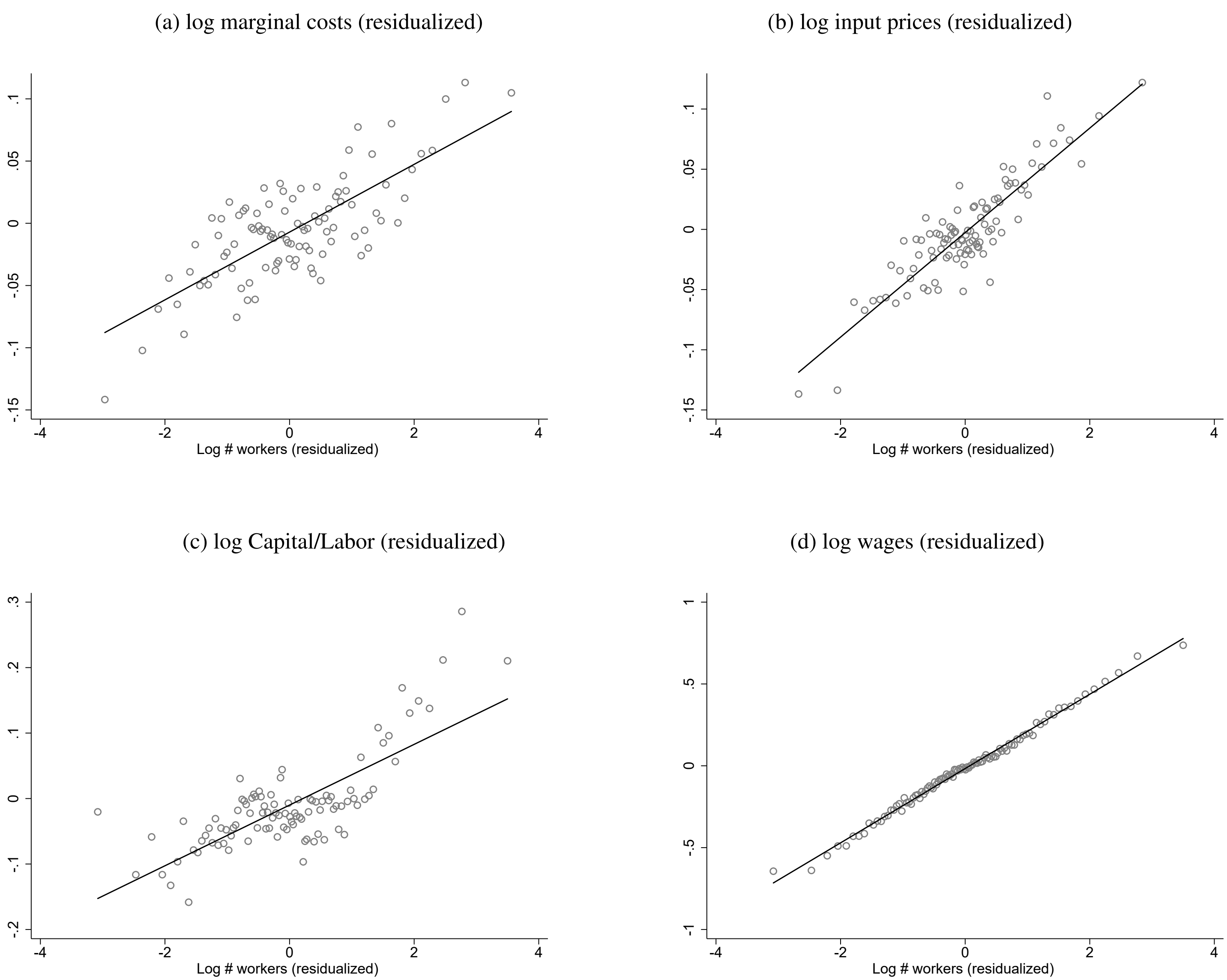
Notes: The figure plots relationship between transportation expenses (per unit of sales) incurred by firms and the size of its labor force during the year 1998 (only year for which information on transportation expense is available). Both axes plot de-meaned values of the variables after controlling for product fixed effects and district fixed effects. The slope of the line is -.0002 (t = -0.6). Mean of y-variable is 0.009 (median 0.0003); mean of x-variable is 4.72 (median 4.78). Standard errors are clustered at district level. Source: ASI

Figure A.2: Share of agricultural population and average income in district



Notes: The figure plots the relation between share of population involved in agricultural activities and average income in the district. Both axes are residualized values after removing state fixed effects and controlling for (log) total population of the district. The correlation is -0.11 significant at 1% levels (t = -11.2) when standard errors clustered at district level. Source: NSS

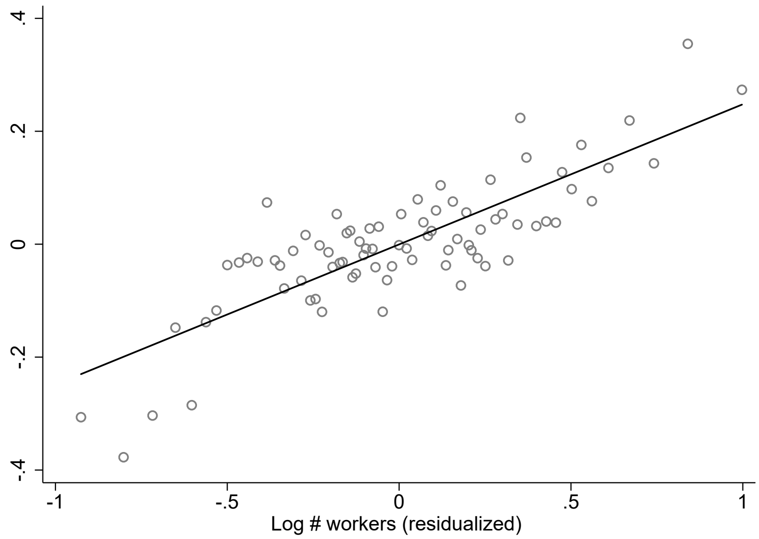
Figure A.3: Relation between firm size and input factors



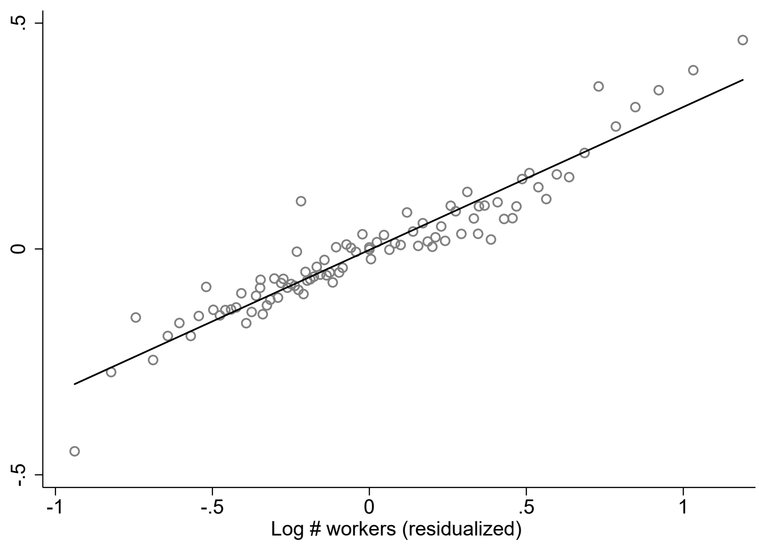
Notes: The figure shows the relation between average firm's log per-unit deviations in marginal cost (Panel (a)), input prices (Panel (b)), capital intensity (Panel (c)), wages per unit labor (Panel (d)) and firm's size (as measured by its labor force). The *y*-axis depicts the residuals of a regression of log per-unit markups or marginal costs on district-by-product-by-year fixed effects. The *x*-axis depicts the residuals of a regression of firm's log number of workers on district-by-(output)product-by-year fixed effects. Each dot represents 1% of observations. Source: ASI

Figure A.4: Relation between firm size and prices (Unorganized Manufacturing Sector Data)

(a) Log output prices (residualized)

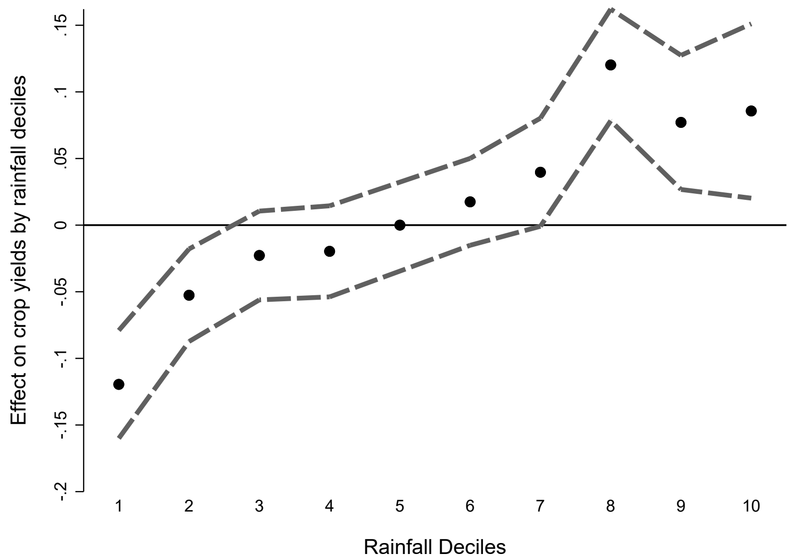


(b) Log input prices (residualized)



Notes: The figure shows the relation between average firm's log per-unit deviations in output prices (top panel), input prices (bottom panel) with firm's size (as measured by its labor force). The *y*-axis depicts the residuals of a regression of dependent variable on district-by-product fixed effects. The *x*-axis depicts the residuals of a regression of firm's log number of workers on district-by-(output)product fixed effects. Each dot represents 1% of observations. Source: NSS Unorganized Manufacturing Sector Survey (2005-06)

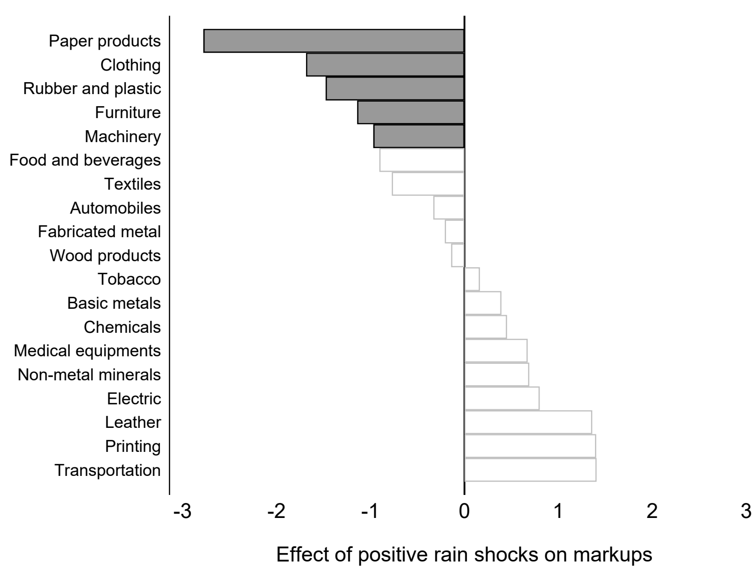
Figure A.5: Effect of rain shocks on agricultural yields



Notes: The figure plots coefficients and 95% confidence intervals from a regression of log crop yields on dummies for each decile of the rainfall distribution within the district. Log crop yields is the log of a weighted average of yields of the 15 crops for which data is available in the VDSA database. The yield for each crop has first been normalized by the mean yield of that crop in the district. Weights are the mean percentage of land area planted with a given crop in a district. Each decile dummy equals 1 if monsoon rainfall in the current year fell within the given decile of the district's usual rainfall distribution for that year and equals 0 otherwise. The omitted category against is the 5^{th} decile. Each regression contains district and year fixed effects. Standard errors are clustered at district level.

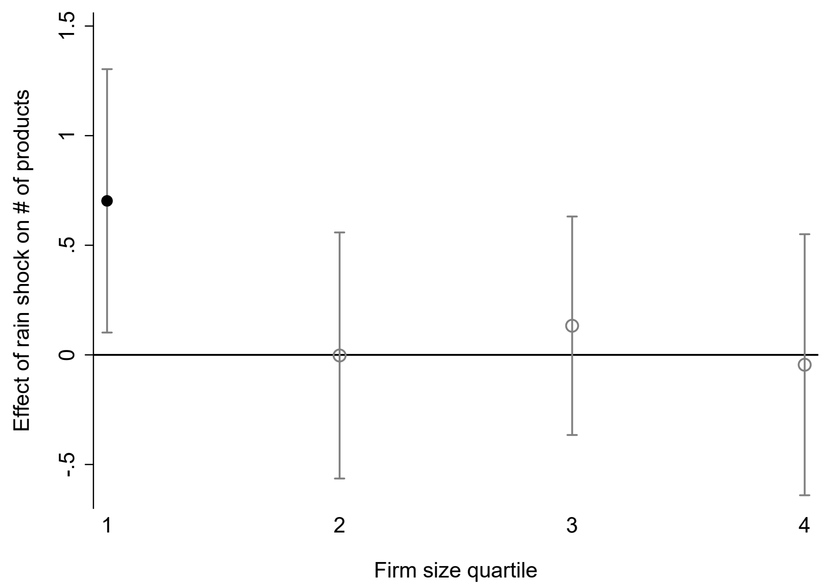
Figure A.6: Effect of rain shocks on markups

Effects across 2-digit industries



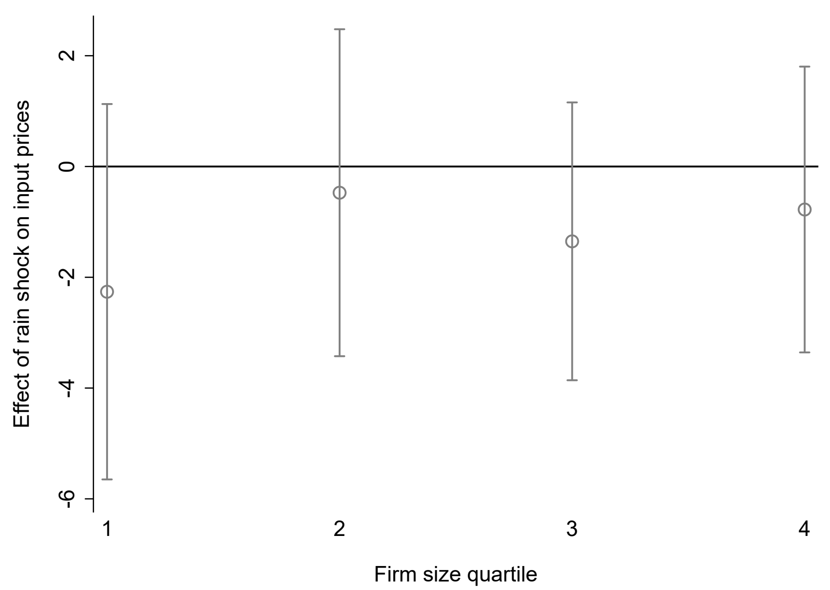
Notes: Gray bars indicate results that are significant at the 10% level and hollow bars represent statistically insignificant from 0 at 10% level.

Figure A.7: Effects of rain shocks on number of products



Notes: The figure reports the heterogeneous effects of rainfall shocks on number of products based on specification: $\log y_{jidt} = \alpha_{ji} + \alpha_{jt} + \sum_{r=1}^{4} \beta^r . (\text{Shock}_{dt} \times Q_i^r) + \Gamma' X_{jidt} + \varepsilon_{jidt}$, where y_{ijdt} is the outcome of interest for firm i in district d in year t. Shock_{dt}^{+} and Shock_{dt}^{-} takes the value of 1 if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. Q_i^r are dummy variables taking the value of 1 when firm i belongs to size quartile r within the industry k.

Figure A.8: Effects of rain shocks on input prices by firm size

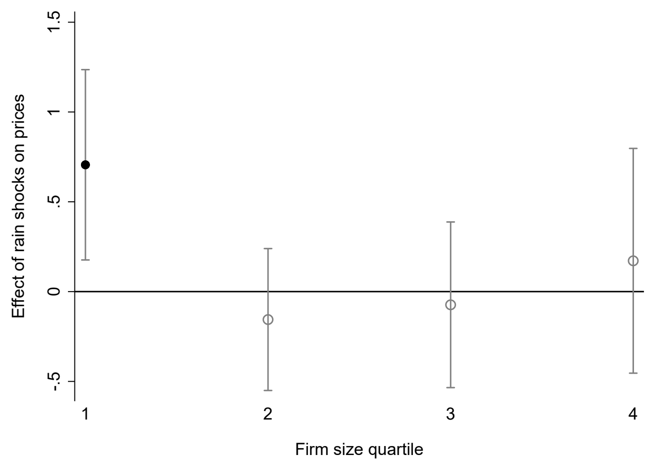


Notes: The figure reports the heterogeneous effects of rainfall shocks on input prices produced by firm. Specification is based on Figure A.7 but instead conducted at the firm-product level.

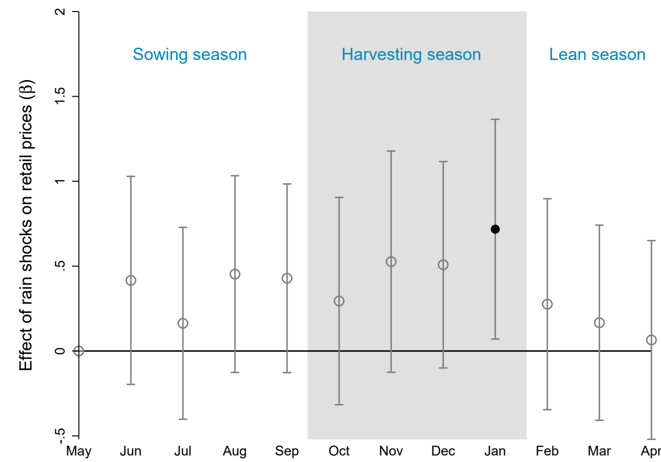
Figure A.9: Effects of placebo and past rain shocks on prices

(i) **Placebo (next year's) rain shocks**

(a) Wholesale prices (ASI data)

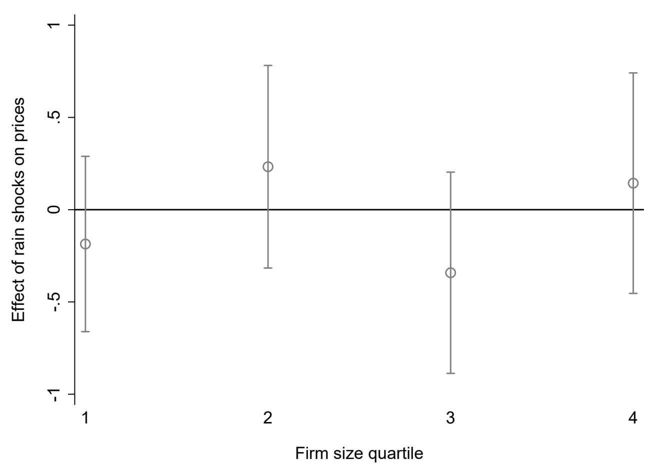


(b) Retail prices (RPU data)

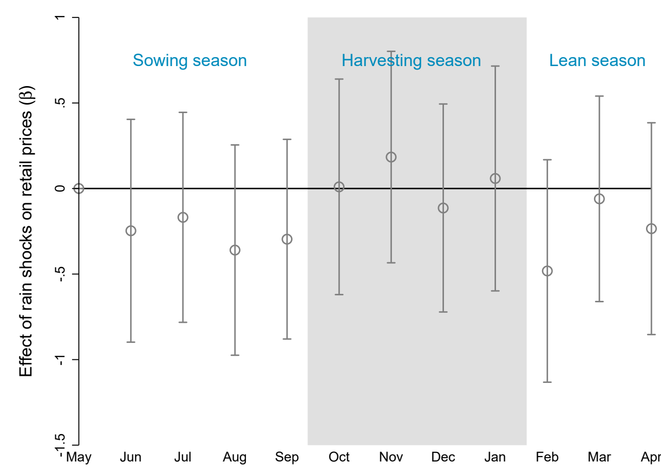


(ii) **Lagged (previous year's) rain shocks**

(a) Wholesale prices (ASI data)



(b) Retail prices (RPU data)



Notes: The figure reports estimates from placebo rain shocks (falsification tests) that uses future rainfall shocks; and estimates of last year rain shocks on prices.

Table A.1: Problems faced by manufacturing firms in the last year

	Dependent variable:					
	1(Faced any problems = 1)			**1**(Observed fall in demand = 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Rain shock this year (-1/0/+1)	-0.070***			-0.018***		
	[0.016]			[0.006]		
Drought this year		0.097***			0.044***	
		[0.031]			[0.010]	
Drought this year						
× First size quartile			0.112***			0.041***
			[0.029]			[0.012]
× Second size quartile			0.085***			0.052***
			[0.032]			[0.013]
× Third size quartile			0.120***			0.039***
			[0.042]			[0.013]
× Fourth size quartile			0.051			0.054***
			[0.042]			[0.011]
Observations	90,376	90,376	90,376	90,376	90,376	90,376
R-squared	0.031	0.027	0.035	0.013	0.014	0.018
Industry f.e.	✓	✓	✓	✓	✓	✓
Size-quartile f.e.			✓			✓

Notes: The table test whether local rain shocks generate operational problems or variation in demand for manufacturing plants located in the district. The average effects report the coefficient β from the estimation of:

$$y_{id} = \alpha_k + \beta \ . \ \text{Shock}_{dt} + \Gamma' X_{id} + \varepsilon_{id}$$

Column (3) and (6) report the effects by firm size from the specification:

$$y_{id} = \alpha_k + \sum_{r=1}^{4} \beta^r \ . \ (\text{Shock}_{dt} \times Q_i^r) + \sum_{r=1}^{4} \gamma_r \ . \ Q_i^r + \Gamma' X_{id} + \varepsilon_{id}$$

For Columns (1)-(3), y_{ik} takes the value 1 if firm i in industry k located in district d reported facing any problem with its operation and 0 otherwise. For Columns (4)-(6), y_{ik} takes the value 1 if the firm reports facing a drop in demand as specific reason of the problem and 0 otherwise. Shock$_{dt}$ (rain shock this year) is defined as +1(-1) if the rainfall in the monsoon months is above(below) the 80th(20th) percentile of the district's usual distribution for monsoon rainfall. It takes the value of 0 if the rainfall is between 20th-80th percentile of district's usual distribution. Drought this year takes the values of one if Shock$_{dt}$ takes the value of -1) and zero otherwise. All columns include 2-digit industry fixed effects and controls for firm's age. Column (1) and (4) also include as control rain shocks in last three years. Column (2)-(3) and (5)-(6) also include as control drought indicator for last three years. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Baseline Correlations: Alternative measures of firm size and product prices

	Output product prices			Factor input prices		
Panel A.	Price	Marg. Cost	Markup	Material Inputs	K/L	Wages
	(1)	(2)	(3)	(4)	(5)	(6)
(log) sales	0.075***	0.020***	0.055***	0.048***	0.246***	0.164***
	[0.003]	[0.005]	[0.004]	[0.008]	[0.004]	[0.002]
Panel B.	Price	Marg. Cost	Markup	Material Inputs	K/L	Wages
	(7)	(8)	(9)	(10)	(11)	(12)
(log) assets	0.056***	-0.011***	0.067***	0.049***	0.614***	0.119***
	[0.003]	[0.004]	[0.002]	[0.006]	[0.005]	[0.002]
Observations	167,221	167,221	167,221	443,022	167,221	167,221
Industry f.e.	✓	✓	✓	✓	✓	✓
District-prod.-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table reports the correlation from Table II using alternate definition of firm size based on total sales (Panel A) and capital (Panel B). Coefficients are reported from reported regression for each independent variable and is based on the following specification: $\log y_{fp} = \alpha_{dp} + \beta \ \log(\text{firm size})_f + u_{fp}$. Standard errors are clustered by district level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Worker's education levels across firm's size distribution

	Workers's Education level				
# workers in employing plant:	No School (1)	Grades 1 to 8 (2)	Grades 9 to 12 (3)	College (4)	Average Daily Wage (in INR)
$L < 6$	0.37	0.36	0.19	0.08	47.81
$6 \leq L < 9$	0.28	0.30	0.24	0.18	68.04
$10 \leq L < 20$	0.21	0.26	0.24	0.29	87.63
$L \geq 20$	0.15	0.23	0.30	0.32	121.45
Average Wage (INR)	37.66	54.20	98.75	143.92	77.49

Notes: This table reports the distribution of workers with different firm size categories by their educational level. The last row reports the mean daily wages for workers in that particular educational group. The last column reports the mean daily wages for workers working for a manufacturing firm that belongs to a particular size distribution. The data is from 1999-2000 NSS employment surveys and contains 109,377 observations.

Table A.4: Estimates of price-elasticity of demand (σ)

	OLS	IV	IV
	(1)	(2)	(3)
(1- σ) All households	-0.408***	-0.577***	-
	[0.022]	[0.031]	-
(1- σ) Poorest Quintile (Relative to Richest)	-	-	-0.726***
	-	-	[0.044]
(1- σ) 2nd poorest Quintile (Relative to Richest)	-	-	-0.696***
	-	-	[0.040]
(1- σ) Median Quintile (Relative to Richest)	-	-	-0.602***
	-	-	[0.039]
(1- σ) 2nd richest Quintile (Relative to Richest)	-	-	-0.504***
	-	-	[0.032]
Observations	103,767	103,767	103,767
R-squared	0.484		
F-stat		82.607	12.555
Region-product f.e.	✓	✓	✓
Quintile f.e.	✓	✓	✓

Notes: The table reports the estimate of price-elasticity of demand based on the estimating equation :

$$\log\left(\frac{x_{ir}(z)}{x_{jr}(z)}\right) = \alpha_{ir} + \alpha_z + (1-\sigma(z))\log\left(\frac{p_{ir}}{p_{jr}}\right) + \nu$$

where i is a product variety, h is a household in region r surveyed in year t. $x_{ir(z)}$ is the total amount spent by an household in income group z on product variety i and p_{ir} is the price of the variety. Column (1) estimates are based on the OLS specification. Column (2)-(3) estimates are based on the IV specification that instruments Δp with state-level leave out mean price changes : $\frac{1}{N-1}\sum_{r'\neq r}\Delta log(p_{ri})$. Standard errors clustered at district level are reported in brackets. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Robustness to definition of rain shocks

	Percentile cut-off for Positive/Negative Shocks				Deviations
	80/20 (baseline)	80/30	85/15	90/10	from the median
	(1)	(2)	(3)	(4)	(5)
	Wholesale prices (ASI Data)				
	Panel A. log (price) × 100				
Rain shock this year	-0.441**	-0.512***	-0.437**	-0.494**	-0.152**
	[0.190]	[0.178]	[0.205]	[0.228]	[0.063]
Observations	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓
	Panel B. log (markup) × 100				
Rain shock this year	-1.144*	-0.742	-1.244*	-1.216	-0.479**
	[0.664]	[0.630]	[0.727]	[0.932]	[0.216]
Observations	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓
	Panel C. log (marginal cost) × 100				
Rain shock this year	0.700	0.229	0.805	0.723	0.326
	[0.749]	[0.719]	[0.829]	[1.034]	[0.254]
Observations	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓
	Retail prices (RPU Data)				
	Panel D. log (retail prices) × 100				
Rain shock this year	-0.235***	-0.317**	-0.445**	-0.826***	-0.113***
	[0.089]	[0.137]	[0.178]	[0.210]	[0.043]
Observations	147,447	147,447	147,447	147,447	147,447
District-product f.e.	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓

Notes: Standard errors clustered at district level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Testing for serial correlation in rainfall

	$\text{RainDeviation}_{d,t}$			
	1998-2009 (Sample Years)		1990-2014	
	(1)	(2)	(3)	(4)
$\text{RainDeviation}_{d,t-1}$	-0.007	-0.007	-0.013	-0.014
	(0.029)	(0.028)	(0.015)	(0.015)
$\text{RainDeviation}_{d,t-2}$	-	0.007	-	0.016
	-	(0.030)	-	(0.012)
Observations	3,116	3,116	7,850	7,850
R-squared	0.231	0.231	0.261	0.261
District f.e.	✓	✓	✓	✓
Year f.e.	✓	✓	✓	✓

Notes: This table tests for serial correlation in rainfall. The unit of observation is district-year and the results are based on 1998-2009. Rainfall data is from University of Delaware. Standard errors are clustered at the district level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Firm's entry/exit in response to rain shocks

	1(entry)	1(exit)	1(entry)	1(exit)
	(1)	(2)	(3)	(4)
Positive shock this year	0.001	-0.001	-	-
	[0.002]	[0.001]	-	-
Positive shock last year	0.002	-0.003***	-	-
	[0.002]	[0.001]	-	-
Drought this year	-	-	-0.002	-0.001
	-	-	[0.002]	[0.001]
Drought last year	-	-	-0.001	0.001
	-	-	[0.002]	[0.001]
Observations	226,275	226,275	226,275	226,275
R-squared	0.358	0.312	0.358	0.312
Firm f.e.	✓	✓	✓	✓
Year f.e.	✓	✓	✓	✓

Notes: The table reports the estimates of new firm entry or incumbent exit based on specification:

$$1(entry/exit)_{it} = \alpha_i + \alpha_t + \beta \text{Shock}_{dt} + \varepsilon_{idt}$$

where 1(entry) takes the value of 1 in the first year of firm's operation and 1(exit) takes the value of 1 when a firms is reported to be Closed in the survey. Standard errors are clustered at the district level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Robustness to financial frictions

	log (markup) × 100			
	(1)	(2)	(3)	(4)
Shock$_{dt}$ (-1/0/+1)				
× First size quartile	-0.312	-0.312	-0.300	-0.273
	[0.333]	[0.311]	[0.347]	[0.358]
× Second size quartile	-0.900***	-0.897***	-0.910***	-0.885***
	[0.273]	[0.271]	[0.280]	[0.276]
× Third size quartile	-0.674**	-0.667**	-0.726***	-0.688**
	[0.283]	[0.281]	[0.277]	[0.281]
× Fourth size quartile	0.131	0.143	0.088	0.142
	[0.354]	[0.352]	[0.396]	[0.413]
Shock$_{dt}$ (-1/0/+1)				
× Cash Ratio	-0.355	-	-	-0.397
	[1.461]	-	-	[1.537]
× Leverage	-	-0.038	-	-0.037
	-	[0.027]	-	[0.027]
× HP-measure	-	-	0.015	0.004
	-	-	[0.107]	[0.110]
Observations	132,746	132,746	130,751	130,678
Firm-product f.e.	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓

Notes: The table tests for robustness of estimates after controlling for differential effect of rain shock based on firms' financial strength. The specification is the one reported in Table VIII with the additional controls of measures of financial constraints interacted with rain shock. Standard errors clustered at district level are reported in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Effect of Rain Shocks on Migration Rates

	Has not moved (Last six months)			
	All	Rural	All	Rural
	(1)	(2)	(3)	(4)
Rain shock this year (-1/0/+1)	-0.073	-0.066	-0.175	-0.194
	[0.123]	[0.161]	[0.123]	[0.146]
Rain shock last year	-0.166	-0.076	-0.149	-0.120
	[0.122]	[0.157]	[0.122]	[0.157]
Observations	964,000	617,801	964,000	617,801
Round f.e.	✓	✓	✓	✓
District f.e.			✓	✓

Notes: The table reports regression estimates of regressions in which the dependent variable is has not moved from district in the past 6 months or more, and the independent variable is rain shocks. Standard errors clustered at district level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Robustness: Larger Unit of Observation (State-level rain shocks)

	Dependent variable: (log of) × 100					
	price	markup	marg. cost	price	markup	marg. cost
	(1)	(2)	(3)	(4)	(5)	(6)
Shock_{st} (-1/0/+1)	-0.763**	-0.939	0.169	-	-	-
	[0.281]	[0.672]	[0.702]	-	-	-
Rain deviations	-	-	-	-0.192**	-0.668**	0.473
from median_{st}	-	-	-	[0.088]	[0.291]	[0.307]
Observations	133,094	133,094	133,094	133,094	133,094	133,094
Firm-product f.e.	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table analyzes the effect of rain shocks calculated at state-level on prices, markups and marginal costs of manufacturing firms. Standard errors clustered at district level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A.11: Effect of rain shocks on prices of exporters

	Dependent variable: (log of) × 100					
	price	markup	marg. cost	price	markup	marg. cost
	(1)	(2)	(3)	(4)	(5)	(6)
Shock_{dt} (-1/0/+1)	0.768	1.732	-0.975	-	-	-
	[1.099]	[2.935]	[3.193]	-	-	-
Rain deviations	-	-	-	0.419	0.578	-0.158
from median_{dt}	-	-	-	[0.418]	[1.008]	[1.159]
Observations	10,114	10,114	10,114	10,114	10,114	10,114
Firm-product f.e.	✓	✓	✓	✓	✓	✓
Product-year f.e.	✓	✓	✓	✓	✓	✓

Notes: The table analyzes the effect of rain shocks on prices, markups and marginal costs of exporting manufacturing firms. Standard errors clustered at district level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

B Markup Estimation for multiproduct firms

This section provides detail on the procedure for estimating markups in the ASI manufacturing data. The framework primarily builds upon the methodology proposed in De Loecker et al. (2016) for estimating markups in multiproduct firms.

A. Framework

Consider a production function for firm f and product j:

$$Q_{fjt} = F_{jt}(V_{fjt}, K_{fjt})A_{ft}$$

To avoid any price-bias, we estimate these in input and output quantities (rather than sales and expenditure in previous section). We add two more assumptions along with (a), (b),(c) assumptions above: (d) expenditure to all variables and fixed inputs are attributable to products (f) firm minimize cost taking quantity and input prices as given. The markup expression in this case is dependent on product j and becomes:

$$\mu_{fjt} = \theta^{v}_{fjt}\left(\alpha^{v}_{fjt}\right)^{-1}, \qquad \underbrace{\theta^{v}_{fjt} = \frac{\partial \log Q_{fjt}(.)}{\partial \log V_{fjt}}}_{\text{Through production function estimation}} \quad , \quad \underbrace{\alpha^{v}_{fjt} = \frac{W^{v}_{fjt}V_{fjt}}{P_{fjt}Q_{fjt}}}_{\text{Only observe for single product firms}}$$

In addition to the fact that we don't observe θ^{v}_{fjt}, the main concern is that for multi-product firms we do not observe α^{v}_{fjt}. We eventually estimate markup as per

$$\hat{\mu}_{fjt} = \hat{\theta}^{v}_{fjt}\frac{P_{fjt}Q_{fjt}}{\exp(\hat{\rho}_{fjt})\tilde{X}^{v}_{ft}}$$

where ρ is the share of input expenditure attributable to product j. Thus we need estimates $(\hat{\theta}_{fjt}, \hat{\rho})$ and have information on $(P_{fjt}, Q_{fjt}, \tilde{X}^{v}_{ft})$ in the data ($\tilde{X}^{v}_{ft}$ is the total expenditure by the plant on variable input). Calculation of $\hat{\theta}_{fjt}$ involves estimation of production function parameters ($\hat{\rho}$,$\hat{\beta}$). Thus $\hat{\theta} \equiv \theta(\hat{\beta}, \tilde{x}_{ft}, \hat{w}_{fjt}, \hat{\rho}_{fjt})$.

B. Estimation

I allow for measurement error and unanticipated shocks to output through $(\exp(\varepsilon_{fjt}))$ i.e. $q_{fjt} = \ln(Q_{fjt}\exp(\varepsilon_{fjt})) = \ln(F_{jt}(V_{fjt}, K_{fjt})A_{ft}\exp(\varepsilon_{fjt}))$. Thus

$$q_{fjt} = f_{jt}(v_{fjt}, k_{fjt}; \beta) + a_{ft} + \varepsilon_{fjt} \equiv f_{jt}(x_{fjt}; \beta) + a_{ft} + \varepsilon_{fjt}$$

Just changes to output over time across due to either (i) changes in input quantities or (ii) unanticipated shocks. Here $x_{fjt} = \{v_{fjt}, k_{fjt}\}$ is a vector of (log) physical inputs and $a_{ft} = \log(A_{ft})$. Another change here is that q_{fjt} is in physical units of output. This eliminates the concerns of a price bias that arises if output is constructed by deflating firm revenues by an industry-level price index.

An important point to note is that we only observe input expenditure and not quantities we need to modify the equation above by using the input expenditure

$$x_{fjt} = \rho_{fjt} + \tilde{x}_{ft} - w^x_{fjt}, \quad \text{using} \quad W^x_{fjt} X_{fjt} = \tilde{\rho}_{fjt} \left[\sum_j W^x_{fjt} X_{fjt} \right] = \tilde{\rho}_{fjt} \tilde{X}_{ft}$$

where $\tilde{x}_{ft}$ is the firm-level expenditure on input x and w^x_{fjt} is the deviation of the unobserved (log) firm-product-specific price from the (log) industry-wide input price index. This leads to production equation to be modified to

$$q_{fjt} = f_j(\tilde{x}_{ft};\beta) + \underbrace{A(\rho_{fjt},\tilde{x}_{ft},\beta)}_{\text{Input Allocation Bias}} + \underbrace{B(w_{fjt},\rho_{fjt},\tilde{x}_{ft},\beta)}_{\text{Input Prices Bias}} + a_{ft} + \varepsilon_{fjt}$$

The main objective is to address the two sources of biases : “Input Allocation Bias” and “Input Prices Bias”.

1. Address Input Allocation Bias

We address this by focusing on single product firm as for these firms $\rho_{pjt} = 1$ and hence $A(.) = 0$ i.e. the true production function will not suffer from input allocation bias. We can also drop sub-script j as it is a single product plant

$$q_{ft} = f(\tilde{x}_{ft};\beta) + \underbrace{B(w_{ft},\tilde{x}_{ft},\beta)}_{\text{Input Prices Bias}} + a_{ft} + \varepsilon_{ft}$$

Three input in the (deflated) input expenditure vector $\tilde{x}_{ft}$: labor ($\tilde{l}$), materials ($\tilde{m}$) and capital ($\tilde{k}$). Thus $\tilde{x}_{ft} = \{\tilde{l}_{ft}, \tilde{m}_{ft}, \tilde{k}_{ft}\}$. We need to address the selectivity (i.e. entry and exit) into single-product firms.

2. Unobserved Input Prices

Treatment of unobserved input prices (as we only see expenditure and not quantities) . In fact, just using the data on quantities is not informative as firm producing high quality product might use different input than lower quality firms. To address this, we do the following:

1. Input price function depends on firms location G_f and input quality v_{ft}. Information on input quality can be obtained from few firm specific variables such as output price p_{ft}, market share ms_{ft}, product dummies D_f, location G_f and in my case rainfall shocks that can cause some structural changes r_{ft}. Notice that there is no j for firm-product as we are focusing on a single-product firm. We assume an input price control function

$$w^x_{ft} = w_t(p_{ft}, ms_{ft}, D_f, G_f, r_{ft})$$

Ideally you would want it to be estimated for all the firm-inputs x. For now, we assume same control function for all inputs. The input price bias function now takes the form

$$B(w_{ft},\tilde{x}_{ft},\beta) = B((p_{ft},ms_{ft},D_f,G_f,r_{ft})\times\tilde{x}^c_{ft};\beta,\delta) \quad \text{where} \quad \tilde{x}^c_{ft} = \{1,\tilde{x}_{ft}\}$$

3. Address Unobserved Productivity and Selection Criteria

Here just follow literature on production function estimation and control for unobserve productivity a_{ft} using static input demand equation for materials

$$\tilde{m}_{ft} = m_t(a_{ft},\tilde{k}_{ft},\tilde{l}_{ft},z_{ft}) \quad \text{where} \quad z_{ft} = \{G_f,r_{ft},p_{ft},D_f,ms_{ft}\}.$$

Inverting this gives us a control function for productivity:

$$a_{ft} = h_t(\tilde{x}_{ft},z_{ft})$$

4. Productivity Process, Moment Conditions and Identification

To estimate the parameter vectors β and δ we form moments based on innovation in productivity shock ξ_{ft} (*SP* is the probability of remaining single-product):

$$a_{ft} = g(a_{ft-1},r_{ft-1},SP_{ft}) + \xi_{ft}$$

Here including rainfall shock r_{ft} say that they *may* affect productivity but does not imply that they *necessarily* would. We now follow the same steps as in the firm-level markups

1. Use the original production equation with input price bias and run the first stage

$$q_{ft} = \phi_t(\tilde{x}_{ft},z_{ft}) + \varepsilon_{ft} \quad \text{where} \quad \phi_t(.) = f(\tilde{x}_{ft};\beta) + B(w_{ft},\tilde{x}_{ft},\beta) + a_{ft}$$

2. Get productivity as a function of (β,δ)

$$a_{ft}(\beta,\delta) = \hat{\phi}_{ft} - f(\tilde{x}_{ft};\beta) - B((p_{ft},ms_{ft},D_f,G_f,r_{ft})\times\tilde{x}^c_{ft};\beta,\delta)$$

3. Get the innovation in productivity as function of (β,δ) using the law of motion of productivity

$$\xi_{ft}(\beta,\delta) = a_{ft}(\beta,\delta) - E(a_{ft}(\beta,\delta)|a_{ft-1},r_{ft-1},SP_{ft})$$

4. Build moment conditions that identify the parameters

$$E(\xi(\beta,\delta)Y_{ft}') = 0$$

where $\quad Y_{ft} = \{m_{ft-1},l_{ft},k_{ft},z_{ft-1}\}\quad$ along with the higher order terms and interactions

5. Recovering Input allocation for multiproduct firms

Recall that we need to now calculate $\rho_{fjt} = \ln \frac{W^X_{fjt} X_{fjt}}{\tilde{X}_{ft}}$ $\forall X \in \{V, K\}$. We first eliminate unanticipated shocks and measurement error as before using $\hat{q}_{fjt} \equiv E[q_{fjt} | \phi_t(\tilde{x}_{ft}, z_{ft})]$. We can write the production function as

$$\underbrace{\hat{q}_{fjt}}_{\text{First stage estimation}} = f(\tilde{x}_{ft}, \hat{\beta}, \hat{w}_{fjt}, \rho_{fjt}) + a_{ft}$$

As our production function is in a translog, we can use the estimation of $\hat{\beta}$ to decompose this translog into a component separately dependent on ρ_{fjt}.

$$\hat{\omega}_{fjt} \equiv \underbrace{\hat{q}_{fjt} - f_1(\tilde{x}_{ft}, \hat{\beta}, \hat{w}_{fjt})}_{\text{Know this from first stage + estimation of } \beta} = f_2(\tilde{x}_{ft}, \hat{w}_{fjt}, \rho_{fjt}) + a_{ft}$$

where we have $\hat{w}_{fjt}$ from the input price estimation. Using the translog functional form for the production function, we obtain:

$$\hat{\omega}_{fjt} = a_{ft} + \hat{a}_{fjt}\rho_{fjt} + \hat{b}_{fjt}\rho^2_{fjt} + \hat{c}_{fjt}\rho^3_{fjt}$$

This gives us $J+1$ equations in $J+1$ unknowns $(a_{ft}, \rho_{f1t}, ..., \rho_{fJ_t t})$ for each firm-year. Recall that these $(\hat{a}_{fjt}, \hat{b}_{fjt}, \hat{c}_{fjt})$ are functions of $(\hat{\beta}, \hat{w}_{fjt})$.

Finally, from here the markups (using materials as the variable inputs) can be obtained using

$$\hat{\mu}_{fjt} = \hat{\theta}^M_{fjt} \frac{P_{fjt} Q_{fjt}}{\exp(\hat{\rho}_{fjt}) \tilde{X}^M_{ft}}$$

Table B.12 displays the mean and median markups across each two digit industry in the manufacturing sector. The mean markup is 2.84 and the median markup is 1.50 with a standard deviation of 5.65, suggesting wide variation in markups across firms. These averages, however, mask considerable heterogeneity across industries. For example, the median markup about 1 in non-metallic minerals, whereas it is 2.42 for firms in industries that produce computing equipment.

I perform two exercises to validate these measures for markup and marginal costs. First, I examine how markups vary with exporting behavior of the firm. The analysis is guided by the literature documenting that markups are systematically higher for exporting firms as compared to domestic firms (De Loecker and Warzynski (2012); Atkin et al. (2017)), and that markups increase upon entry into export market. Table B.13 test for these patterns in the data using measures of estimated markups. As shown in Columns (1) to (3) of the table, markup estimated from ASI data are higher for exporter relative to non-exporter. Moreover, Columns (4) to (6) show that markups are also increased in share of sales exported by the firms. These estimates remain robust and significant if one focuses on within-firm variation after controlling for firm fixed effects.

Second, I analyze how markups and marginal costs vary across products within a firm based on their share of sales. Literature on multiproduct firms feature a core competency for these firm wherein their core product has the lowest marginal cost (Mayer et al. (2014); De Loecker et al. (2016)). Mayer et al. (2014) assume a linear demand system implying variable markup across products, implying that the

Table B.12: Markups, by industry

Industry	Markups Mean	Markups Median	Industry	Markups Mean	Markups Median
Food and beverages	1.46	1.10	Non-metallic minerals	1.30	0.97
Tobacco products	2.53	2.37	Basic metals	2.52	1.80
Textiles	2.54	1.75	Fabricated metal	3.75	1.82
Clothing	3.14	1.08	Machinery	6.23	2.16
Leather products	4.15	1.93	Electrical mach. & comm.	3.87	1.76
Wood products	3.67	1.94	Medical equipments	5.83	2.42
Paper products	1.28	1.17	Automobiles	5.50	1.60
Printing and publishing	3.19	1.42	Other transportation	3.35	1.29
Chemicals	3.38	1.77	Furniture	2.66	1.50
Rubber and plastic	3.72	1.34	**Total**	**2.84**	**1.50**

Notes: The table displays the mean and median markups across 2-digit industries between 1998-2009. The tables trims observations that are below and above 5th and 95th percentile in each industry.

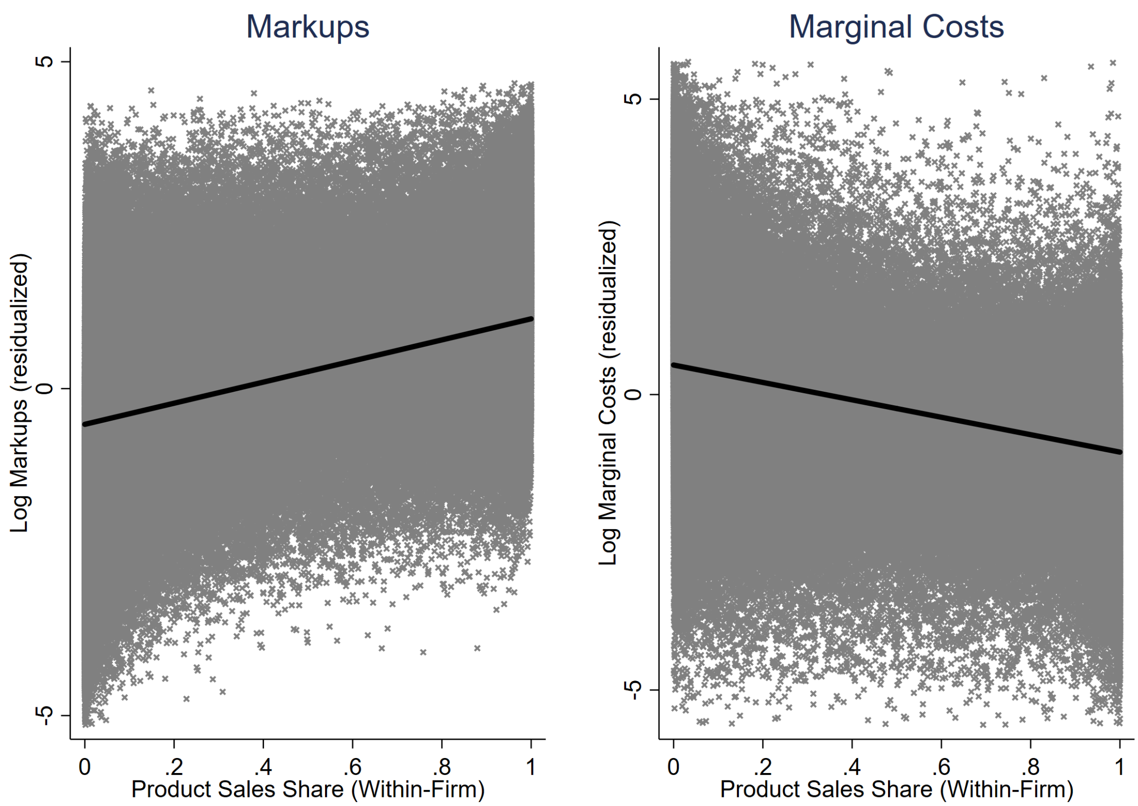
Table B.13: Markups and export status

	Dependent variable: log (markup)					
	(1)	(2)	(3)	(4)	(5)	(6)
1(exporter)	0.076***	0.067***	0.060*	-	-	-
	[0.019]	[0.020]	[0.036]	-	-	-
% of sales exported	-	-	-	0.093***	0.091***	0.168**
	-	-	-	[0.033]	[0.034]	[0.073]
Product-year f.e.	✓	✓	✓	✓	✓	✓
District-year f.e.		✓	✓		✓	✓
Firm-product f.e.			✓			✓

Notes: Standard errors clustered by firm are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

markups charged by firms are increasing in the core competency of their products. Figure B.10 provides evidence consistent with these papers. It plots the residual markups and marginal costs (de-meaned using product-year, firm-year and district-year fixed effects) against the share of sales made for that product within each firm. Markups rise as the firm move towards its core competency, whereas the marginal costs decrease. These correlations are remarkably consistent with the multi-product firm literature even without imposing any assumptions on the demand system or market structure in my estimation.

Figure B.10: Markups and marginal costs as share of product sales within-firm, for multiproduct firms



Notes: The figure plots markups, costs as a share of product sales share. Markups and marginal costs are demeaned using product-year, firm-year and district-year fixed effects and outliers are trimmed at above and below 99th percent and 1st percent.

C Alternative Explanations and Robustness

Firms' Entry and Exit. Incumbent firms could lower their markup in during periods of high demand in response to increase firm entry (Jaimovich and Floetotto (2008)). This endogenous supply-side response to cater higher demand increases the competition and exerts downward pressure on markups. Similarly, firms could increase their markup during recessions if lower demand triggers a rise in exits, increasing the market power of surviving firms. Intuitively, firm entry or exit seems an unlikely channel for these results. Establishing a new firm requires substantial capital investment, labor costs etc. and it seems unlikely that firms would incur these large costs given the temporary shift in consumer demand induced by these rain shocks.

I directly test for firm's entry and exit in the data. ASI data reports the year of establishment for firms as well as whether a firm is operational during the survey year. Column (1) to (2) of Appendix Table A.7 shows that there is no evidence of excess entry of firms within a district in response to positive rain shocks; and neither is there a support for firms exiting in years of negative rainfall shocks (Column (3)-

(4)). In both cases, the magnitudes are close to zero and results are not statistically significant. Therefore, firm entry or exit decision do not seem to be driven by these local rain shocks.

New product introduction. Firms might innovate more and introduce new product in response to higher aggregate demand, thus increasing competition faced by firms at the product level (Jaravel (2019)). New product introduction in response to higher demand could put downward pressure on markups for the existing products sold by firms. Two pieces of evidence suggest that this is unlikely the channel for explaining my results. First, based on Jaravel (2019), it is the size of the market, and not the composition of the market, that matters for introduction of new products and thus lower prices in periods of higher demand. Under this hypothesis, the coefficient on the interaction between rain shocks and level of population in the district in specification 13 (β_2) should be negative. Results in Table IX rejects the hypothesis: although statistically insignificant, β_2 is positive.

Second, as argued in Goldberg et al. (2010), introduction of new products or upgrading products is costly. It requires setting up new production lines, investment in plants and machinery, hiring more labor, all for which requires significant fixed upfront costs. Given the temporary nature of these demand shocks, it seems unlikely that firms would incur such steep costs.[34] The ASI data records product entry and exit, allowing me to test this directly. Appendix Figure A.7 shows that only firms in the smallest size quartile increased their product scope in periods of positive rainfall shocks, with no effects on firms in the middle and upper range of size distribution. If product innovation channel was indeed a driving force, one would have expect the price effects to be stronger for smaller firms.

Collusion. If wholesalers are repeatedly competing with one another, then they may tacitly collude on their prices. Bergquist (2019) provides evidence for collusion among traders in agricultural markets in Kenya, and Meenakshi and Banerji (2005) find similar supporting evidence in Indian agricultural markets. In the theoretical models of collusion, like those of Rotemberg and Saloner (1986), countercyclical markups could result from changes in ability of firms to sustain the collusion in times when demand is changing from period to period. For example, a firm will be tempted to renege from a collusive agreement during periods of temporary increase in demand, because the gain from cheating is increasing in current demand but the loss from punishment increases in future demand. While I do not observe collusion explicitly, I present the following two evidences that are inconsistent with prediction from these models.

First, in these models the incentives to deviate from collusive contracts are increasing in demand. Therefore, lower incentives to collude in periods of high demand will affect the prices for firms in the smallest quartile of size distribution, as these firms observe the largest increase in their demand induced by better rainfall. Moreover, the collusion model would predict that rainfall shocks should *lower* prices in districts with *larger* population (i.e. size effect). As shown in previous results, both these predictions are not borne out by the data. Second, the incentive to deviate are based on aggregate demand and therefore firms in *all* product categories should renege on collusive agreements and lower their prices when demand

[34]Moreover, as also argued in Jaravel (2019), the product innovation effects on prices are endogenous supply responses to demand shocks are plausible when firms are able to adjust their supply curve over a longer time horizon.

is high. However, as shown before, the price effects I observe are present in sectors with larger scope of product differentiation.

Consumer Search. Warner and Barsky (1995) suggests that consumers are willing to shop more outlets (or shop across more categories within outlets) during periods of peak aggregate demand. Therefore, consumers appear to be more price sensitive to firms (either retailers or manufacturers) in booms due to increased search activity. Both Warner and Barsky (1995) and the demand composition channel suggest that *firm-level* price elasticity matters, but they emphasize different mechanisms. In the first, time-varying price elasticity is a result of increased search activity ("intensive margin"). In the second, it is a result of change in demand composition ("extensive margin").

The non-monotonic relationship between rainfall induced demand shocks and prices is especially relevant to discriminate between the two channels. Higher search intensity in periods of increased aggregate demand would predict that price elasticities increase is larger for firms that face higher increase in demand. This in turn implies that prices decrease should be stronger among smaller firms, which observe a larger increase in demand. On the other hand, under the demand composition channel demand elasticities increase is larger for firms that observe an increase in their *relative* demand from price sensitive consumers. Conditional on assortative matching documented in this paper, this implies that prices decreases should be stronger among firms in the middle of the size distribution. Since the results support the latter evidence, the view that consumer search activity increases in periods of high demand does hold support in the data.

Financial Frictions. I next explore whether my results are driven by differential degree of financial constraints faced by firms. Papers including Gilchrist et al. (2017) and Chevalier and Scharfstein (1996) document the role of financial frictions for higher markup during periods of low demand. In these papers, firms facing costly external financing under a negative demand shock decide to raise their prices in order to reduce their probability of going bankrupt. Firms are able to do so by increasing their markups and prices in presence of a sticky customer base, allowing them to generate cash in short-run and reduce their probability of bankruptcy. Two results rule our financial frictions as the potential driver for my results.

First, as documented in Columns (1)-(3) of Table A.8 the estimates are robust when I include as control the differential effect of rainfall shocks based on firm's financial strength. I use three measures of financial constraints conventional in the literature: its's cash ratio, leverage and Hadlock and Pierce (2010) measure of financial constraint.[35] The estimates on measure of financial frictions are insignificant and the main estimates remain robust to inclusion of these controls. Column (4) shows the robustness of estimates upon includes all these controls all at once. Second, as documented previously, smallest firms do not change their prices in response to negative shocks. Since the seminal work by Gertler and

[35] These measures are defined as following: (i) Cash ratio $= \frac{\text{Cash}}{\text{Cash + Fixed Assets}}$ (ii) Leverage $= \frac{\text{Debt}}{\text{Fixed Assets}}$. The Hadlock and Pierce (2010) is calculated as following: $\text{SA}_{i,t} = -0.737 \times \log \text{SIZE}_{i,t} + 0.043 \times (\log \text{SIZE}_{i,t})^2 - 0.040 \times \text{AGE}_{i,t}$, where $\text{SIZE}_{i,t}$ denotes inflation-adjusted (in \$ 2004) total assets of firm i in year t and $\text{AGE}_{i,t}$ is the age of the firm, defined as the number of years the firm is listed. In calculating the index, Hadlock and Pierce (2010) winsorize total assets at \$4.5 billion and age at 37 year. They show that this simple and intuitive relation between firm size and age is very robust and accurate in identifying financially constrained firms, with smaller values of the index indicating a smaller likelihood of being financially constrained.

Gilchrist (1994), firm size has been a popular proxy for financial constraints faced by firms with the idea that smaller firms have limited access to financial markets relative to larger firms. Therefore, no price changes for smallest firms is in contrast with the financial frictions channel which suggests that the smallest — and most financially constrained firms — would increase their prices when facing a drop in demand.

Demographic changes. Rural migration could change the population structure of the district. For example, if poor households decide to migrate after rainfall realizations in the district, the market size and composition faced by firms could change for reasons unrelated to changes in demand from the existing customer base.[36] More people could migrate into regions with higher rainfall during the year in response to increase in labor demand in the region.[37] However, inter-district migration rates among rural population in India are extremely low. For example, using NSS data, Topalova (2010) reports that only 3.6 percent of rural population in 1999-2000 reported migrating outside of their districts in the past 10 years. Munshi and Rosenzweig (2016), using Rural Economic Development Survey, also find that rural migration rate is low.

It could still be the case that households temporarily migrate in response to rain shocks. In Table A.9, I use migration data from NSS from year 1999-2000, to regress the migration rate among rural households in response to rainfall shocks. The overall results are consistent with the above data. First, on average less than 2 percent of rural households report having moved outside their villages in the past six months or more. Second, the migration rates do not appear to be driven by rainfall-induced agricultural productivity shocks - the estimated coefficient of migration on rainfall shocks (both positive and negative shocks) is small in magnitude and statistically insignificant. Overall, the results on migration suggest that this is a potential weak channel and is unlikely to drive the price patterns observed in the data.

A. *Robustness checks*

Quality adjustment. Do firms adjust their quality in response to demand shocks to the poor? If firms are operating separate product lines, each for different consumer base, then they could lower their product quality in response to higher demand from poor households demanding lower quality goods. Lower quality could in turn lead to lower prices. On the other hand, increased competition during booms could force firms to improve their price-adjusted quality. This in turn could lead to higher prices. However, it is important to note that while changing product quality have implications for prices, they do not have direct implication for the results on markup cyclicality. This is because, as predicted in Section IV, changes to quality will be reflected directly in the cost structure for the firms. Thus, while quality changes will carry implications for price responses, they will not change the interpretation of the markup responses document previously.

[36] This argument is explored in Lach (2007), who finds that retail prices decreased in short-run across Israelian cities with higher immigrants from Soviet Union relative to the native population. He attributes these negative price responses to different demand characteristics of immigrants relative to natives.

[37] There could be both net in-migration or out-migration in a region in response to positive rain shocks. Net in-migration can be a result of more agricultural laborers migrating to a region in response to increase labor demand on farms. Net out-migration could be caused if agricultural workers migrate away due to alleviation of credit constraint after a positive income shock.

In absence of direct measures of product quality, input prices serve as imperfect signal for the quality of the output. Therefore, any changes to quality by firms will be reflected in the type of input quality — and hence input prices — that the firms source for its production.[38] I test whether firms adjust their quality by examining the effect of rainfall shocks on input prices. Figure A.8 shows that firm's input prices (material inputs) across the size distribution are not changing in response to rain shocks. Thus, firms are not updating their quality in response to changes in rural demand.

Alternative definitions of rain shocks. In this section I show that my results are not sensitive to the definition of rain shocks employed in the main analysis. Table A.5 shows the relevant results. In Column (1) to (4) I use different cut-offs of rain shocks in equation 12: positive and negative shocks are defined as rain shocks above/below 80/30, 85/15 and 90/10 percentiles. In Column (5), I use continuous measure of rain shock defined as rainfall deviation relative to the historical rainfall received in the district. The estimates are similar and consistent in magnitudes to the main results from Table VII, for prices (Panel A), its underlying markups and marginal costs (Panel B and C) and retail prices (Panel D).

In Panel (i) of Figure A.9, I conduct falsification tests using rain shocks realized in the next year rather than the current year. I conduct this exercise for both prices from the ASI data as well as monthly retail price (RPC) data. As one would expect, neither manufacturing prices (Panel (i-a)) or monthly retail prices (Panel (i-b)) are responsive to these placebo shocks.

I next analyze whether demand responses observed from last year's rain shocks have any persistent effects on prices in the current year. Similar to before, I conduct this exercise for both ASI prices as well as prices observed in the RPC data. I do not find any evidence in support of past rain shocks having any persistent effects on future prices: as can be seen in Panel (ii) of Figure A.9, neither of manufacturing prices (Panel (ii-a)) or monthly retail prices (Panel (ii-b)) are responsive to local rain shocks observed in the past year.

Larger Unit of Observation: States. In the empirical analysis conducted so far, I assumed that districts are good approximation of the consumer markets faced by local manufacturing firms. Few potential concerns are that some districts might be too small to capture the complete market for firms; or it could be that firms located on borders of multiple districts cater to consumers residing in all of them. Moreover, the maps shown in Figure VII suggest that rain shocks might be correlated in districts across space: neighbouring districts might be exposed to similar rain shocks. In order to take such concerns into account, I perform the analysis at a larger unit of observation: states . High cross-border state taxes along with a large population base arguably makes the consumer markets for firms restricted to its state of operation (Rotemberg (Forthcoming)). Table A.10 reports the estimates of *state-level* rain shocks on firm-level prices. State-level rain shocks are constructed similar to district-level rain shocks, with the difference that they are based on deviation of average rainfall across all districts in that state from its historical average. The estimates for effects on prices, markups and marginal costs are consistent and

[38] This argument is also central to the test in Bastos et al. (2018). A central assumption with this test is that firms do not have pricing power in the input market.

similar in magnitude to those reported in Table VII, both when using discrete rainfall shocks (Column (1) to (3)) or continuous measure based on rainfall deviations (Column (4) to (6)).

Effects on exporters. I now analyse the effects of rain-induced local demand shocks on exporters. Just like the domestic tradable sector, prices for exporters are a function of the demand that they face in export markets, rather than the local demand. Therefore, exporters should largely be unaffected by the demand shocks. On the other hand, if rain shocks were indeed common supply shocks to firms in a district, we would expect such changes in firm costs to be reflected in its prices. I use the data on ASI exporters to test these hypotheses. Consistent with this hypothesis, Table A.11 documents that prices and its underlying components are not affected by local rain shocks.

D Comparison with existing models on firm heterogeneity

I test the predictions of these two frameworks under both CES demand system and linear demand system. I compare the cross-sectional predictions between firms-size and (a) prices (b) markups (c) marginal costs . In the time-series, I compare the predictions on markup responses made by these models in response to demand shocks to the poorest income group. I summarize these predictions in Table D.14.

Efficiency and Quality Sorting with CES Demand. Melitz (2003) is the backbone of efficiency sorting models with CES demand. Under this framework, more efficient firms have lower marginal costs and set lower prices. A number of studies over the last decade have incorporated in the heterogeneous firms' framework. Under these frameworks, *quality-adjusted* prices follow the similar behavior as Melitz (2003); and more productive and successful firms along charge higher prices for their products. This higher price is a premium for quality and is driven by higher marginal costs: production of better quality entails expensive and better quality inputs. Notable work in this area includes Verhoogen (2008) and Kugler and Verhoogen (2011).

Under CES demand, however, all firms optimally charge a constant markup over marginal costs. Therefore, markups do not vary with firm productivity (or firm size); and neither do they vary across time in response to demand shocks. This holds under both efficiency sorting and quality sorting framework.

Efficiency and Quality Sorting with linear demand. Atkeson and Burstein (2008) and Melitz and Ottaviano (2008) present an efficiency sort model where firms face a nested CES demand and linear demand respectively. Unlike CES preferences, the price elasticity of demand faced by firms is not constant in these models but rather depends on degree of competition among firms in these markets. Firms facing lower competition (i.e. larger firms) charge higher markups. Because of efficiency sorting, larger firms have lower marginal costs and offer lower prices in both these frameworks, even though they have higher markups.

Kneller and Yu (2016) embed quality differentiation in Melitz and Ottaviano (2008). In their setting, they assume that firms with higher marginal costs produce better quality as well as charge higher markup as they are able to larger market share. However, in response to an increase in demand — irrespective of which income group it comes from — the markups increase in these models.

Table D.14: Existing models on firm heterogeneity

		Correlation between firm size and		Δ_t Demand from the poor
Nature of firm heterogeneity, demand	Relevant Papers	Marginal Cost	Markup	Δ_t Markup
Efficiency sorting, CES	Melitz (2003)	-	0	0
Efficiency sorting, Linear	Melitz and Ottaviano (2008)	-	+	0
Quality sorting, CES	Verhoogen (2008) Kugler & Verhoogen (2012)	+	0	0
Quality sorting, Linear	Kneller and Yu (2008)	+	+	+
Quality sorting, CES with heterogeneous demand elasticities	This paper and data	+	+	-

Taken together, this exercise shows that existing models of firm heterogeneity cannot explain the three findings of the paper in combination: (a) larger firms have higher marginal costs (b) larger firms have higher markups (c) markups are decreasing in higher response to demand from the poor. The theoretical framework proposed in Section IV which introduces non-homothetic consumer preferences in quality sorting framework is consistent with these predictions in the data.

E Mathematical Appendix

Proof for Prediction 3 I remove the subscript j for convenience. Define $\zeta_i(\psi_i) = f(\psi_i) \, . \, g(\psi_i)$, where

$$\begin{aligned} f(\psi_i) &= \frac{-1}{\tilde{\sigma}(\tilde{\sigma}-1)} < 0 \\ g(\psi_i) &= \sum_{k \neq i} (\sigma_i - \sigma_k)\psi_k \psi_i > 0 \end{aligned}$$

To see that the function $\zeta_i(\psi_i)$ has a unique minimum, we first solve for $\zeta_i'(\psi_i)$

$$\begin{aligned} \zeta_i'(\psi_i) &= f(\psi_i) \, . \left[f(\psi_i)(2\tilde{\sigma}-1) \left(\sum_{k \neq i} (\sigma_i - \sigma_k)\psi_k \psi_i \right) + \sum_{k \neq i} (\sigma_i - \sigma_k)(\psi_k - \psi_i) \right] \\ &= f(\psi_i) \, . \left[(f(\psi_i)(2\tilde{\sigma}-1) \, . \, \psi_i + 1) \left(\sum_{k \neq i} (\sigma_i - \sigma_k)\psi_k \right) - \psi_i \, . \sum_{k \neq i} (\sigma_i - \sigma_k) \right] \end{aligned}$$

Solving for $\zeta_i'(\psi_i) = f'(\psi_i) \, . \, g'(\psi_i) = 0$ gives

$$(f(\psi_i)(2\tilde{\sigma}-1) \, . \, \psi_i + 1) \left(\sum_{k \neq i} (\sigma_i - \sigma_k)\psi_k \right) = \psi_i \, . \sum_{k \neq i} (\sigma_i - \sigma_k)$$

The left hand side is decreasing in ψ_i and the right hand side is increasing in ψ_i. Therefore, there exists a unique $\psi_i^* \in [0,1]$ for which $\zeta_i'(\psi_i^*) = 0$. Next, we solve for $\zeta_i''(\psi_i)$:

$$\zeta_i''(\psi_i) = f''(\psi_i) \, . \, g(\psi_i) + 2 \, . \, f'(\psi_i) \, . \, g'(\psi_i) + f(\psi_i) \, . \, g''(\psi_i) \tag{18}$$

We can solve for individual components

$$\begin{aligned} f''g &= 2\frac{(f')^2}{f} g + 2f^2 \left(\frac{d\tilde{\sigma}}{d\psi_i} \right)^2 g \\ f'g' &= -\frac{(f')^2}{f} g \\ g''f &= -2 \, . \, f \, . \left[\sum_{k \neq i} (\sigma_i - \sigma_k) \right] \, . > 0 \end{aligned}$$

Substituting these expressions in 18

$$\zeta_i''(\psi_i) = 2f^2 - 2 \, . \, f \, . \left[\sum_{k \neq i} (\sigma_i - \sigma_k) \right] \, . > 0$$

Therefore, ζ_{it} is convex function with a unique minimum.

F Alternative theoretical framework: endogenous demand elasticities

I propose an alternate theoretical framework for variable markups with endogenizes the demand elasticities faced by firms. The framework is based on Atkeson and Burstein (2008) with modification that firms make pricing decision in presence of consumers that have heterogeneous quality valuations. Specifically, when faced with identical prices, rich and poor households allocate their consumption expenditure differently across the quality ladder. The production side follows Kugler and Verhoogen (2011) and features endogenous input and output quality choice across heterogeneous firms. There are I consumer groups and a continuum of S sectors (analogous to the product group in the data). Each sector is populated by a finite set of exogenously given heterogeneous firms. Consumers are indexed by i, sectors by s and firms by j.

A. Demand

There are I consumer groups with a representative consumer in each group with nested elasticity of substitution preferences. The upper nest is on the consumption of goods across sectors and is given by

$$U_i = \left[\int_{s \in S} (X_{is})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{19}$$

where X_{is} is the sector-level aggregate consumption for consumer i given by

$$X_{is} = \left[\sum_{j \in J_s} \left(q_j^{\phi_i} x_{ij} \right)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{20}$$

where q_j is the product quality; x_{js} is the consumption and $\phi_i \equiv \phi(z_i)$ is the taste of quality for consumer i, which I assume to be increasing in level of wealth i.e. $\phi_{poor} < \phi_{rich}$. Following Atkeson and Burstein (2008), I assume that goods are more substitutable within sector than across sectors i.e. $\rho > \eta$. I also assume that both ρ and η are greater than 1.

The consumer group-level and sectoral price indices are given by:

$$P_i = \left[\int_{s \in S} P_{is}^{1-\eta} \right]^{\frac{1}{1-\eta}} \tag{21}$$

$$P_{is} = \left[\sum_{j \in J_s} \left(\frac{p_j}{q_j^{\phi_i}} \right)^{1-\rho} \right]^{\frac{1}{1-\rho}} \tag{22}$$

where p_j is the output price (sales price) charged by firm. Firms do not observe the individual characteristics ϕ_i, and therefore, cannot price discriminate across consumers.

The demand faced by firm j from consumer group i is given by

$$x_{ij} = \left(U_i P_i^{\eta} \right) P_{is}^{\rho-\eta} p_j^{-\rho} q_j^{\phi_i(\rho-1)} \tag{23}$$

The corresponding sectoral market share of firm i is

$$s_{ij} = \frac{p_{ij}x_{ij}}{\sum_{k\in J_s} p_{ik}x_{ik}} = \left[\frac{\left(\frac{p_j}{q_j^{\phi_i}}\right)}{P_{is}}\right]^{1-\rho} = \frac{\left(\frac{p_j}{q_j^{\phi_i}}\right)^{1-\rho}}{\left[\sum_{j\in J_s}\left(\frac{p_j}{q_j^{\phi_i}}\right)^{1-\rho}\right]} \tag{24}$$

Each firm faces a price elasticity of demand from consumer group i :

$$\sigma_{ij} = -\frac{p_i}{x_{ij}}\frac{dx_{ij}}{dp_i} = \rho(1-s_{ij}) + \eta s_{ij} \tag{25}$$

As ϕ_i is the only parameter the varying across consumer groups, we can take derivative of price elasticity of demand w.r.t. ϕ_i

$$\frac{d\sigma_{ij}}{d\phi_i} = -(\rho-\eta)\frac{ds_{ij}}{d\phi_i} \tag{26}$$

where

$$\frac{ds_{ij}}{d\phi_i} = (\rho-\eta)s_{ij}\left[\log q_j - \log\tilde{q}_i\right] \tag{27}$$

where $\tilde{q}_i = \prod_{j\in J_s} q_j^{s_{ij}}$ is the sales-weighted average quality produced in each sector. With quality differentiation, the market share of larger firm is increasing with consumer wealth for firms producing higher quality goods. Among firms selling to wealthier household, firms producing higher quality enjoy higher market share — and therefore — places greater weight on the between-sector elasticity of demand η (as opposed to within-sector elasticity). As $\rho > \eta$ by assumption, firms with greater market sector within a consumer group face lower elasticity of demand from that consumer group.

We can use this consumer segment-wise price elasticity to compute the aggregate price elasticity for the firm. The price elasticity of demand for firm j is the *sales-weighted* average of price elasticity of demand of its consumer base:

$$\tilde{\sigma}_j = \sum_i \sigma_{ij}\psi_{ij} \tag{28}$$

The greater the firm's share of sales made to a particular income group (ψ_{ij}), the higher is the weight places on that group's price elasticity of demand (σ_{ij}). Recall that, as per assortative matching, wealthier households have a tendency to consume more from larger firms. Since σ_{ij} is lower for wealthier households, firms that make larger share of sales to wealthier households (i.e. larger firms) face lower elasticity of demand.

We can compare our expression to the case of (i) no quality differentiation ($q_j = k$ (constant) (ii) no differences in taste for variety ($\phi_i = \phi$). With no quality differentiation, the sector-wise market share is also same for firms i.e. $\sigma_{ij} = \tilde{\sigma}_j = \rho(1-s_j) + \eta s_j$. Therefore, larger firms charge higher markups as in Atkeson and Burstein (2008).

With no differences in taste for variety, there is no consumer heterogeneity. Therefore, each firm makes equal share of its sales to all consumer segments and similar to Atkeson and Burstein (2008) firms with higher market share charge higher markup. The only difference from the above case is that the sector-wise market share is now calculated using quality-adjusted prices.

Therefore, dispersion in consumer's valuation of difference product quality generates excess markup dispersion across firm size distribution. This is consistent with the results in Table III that documented positive correlation between firm-size and markups, with the effects higher in sectors with greater scope of quality differentiation.

B. Production

The production side closely follows Kugler and Verhoogen (2011). I assume that there is perfectly competitive constant-returns-to-scale intermediate input sector with quality differences. It uses labor l to transform in the different quality. The production function is given by $f_I(l,c) = \frac{l}{c}$. Therefore to produce one unit of quality c entails l units of labor. Letting the wage w to be common across firms. Given the perfect competition among intermediate input producers, the price of input quality c is $p_I(c) = wc$.

Final goods producer have productivity ("capability") λ_j, which is exogeneous.The production function for final goods producer if given by

$$f_F(n) = n\lambda^a \tag{29}$$

where n is the number of units of inputs used and $a > 0$. Firms face a fixed cost f_e to operate in the market. This implies that $\frac{1}{\lambda_a}$ units of inputs are used for each physical units of outputs, and hence the marginal cost of each unit of output is $\frac{p_I(c)}{\lambda^a} = \frac{wc}{\lambda^a}$. Following Kugler and Verhoogen (2011), the production of quality in the final-good sector is subject to complementarity between input quality, z_i and technical plant productivity:

$$q_j^* = \left[\alpha\lambda_j^{b\theta} + (1-\alpha)c_j^{\gamma\theta}\right]^{\frac{1}{\theta}} \quad \theta < 0,\ b,\gamma > 0,\ \alpha \in (0,1) \tag{30}$$

where $q_j^* = q_j^{\phi_j^*}$ and $\phi_j^* = \sum_i \frac{x_{ij}}{x_j}\phi_i$. The parameter b captures the technological potential for improving quality with increased productivity and therefore determines the scope for quality differentiation. For simplicity, I assume $\gamma = 2$.

C. Firm's Optimization

Firm's profit is given by

$$\pi_j(p_j, c_j; \lambda_j) = \left(p_j - \frac{wc_j}{\lambda_j}\right)x_j - f_e \tag{31}$$

Optimizing over firm's choice of p_j and c_j gives

$$c_j = \left(2\phi_j^* - 1\right)^{-\frac{1}{2\theta}}\lambda_j^{\frac{b}{2}} \tag{32}$$

$$q_j^* = \left(2 - \frac{1}{\phi^*}\right)^{-\frac{1}{2\theta}}\lambda_j^{\frac{b}{2}} \tag{33}$$

$$p_j^* = \mu_j mc_j = \left(\frac{\tilde{\sigma}_j}{\tilde{\sigma}_j - 1}\right)w\left(2\phi_j^* - 1\right)^{-\frac{1}{2\theta}}\lambda_j^{\frac{b}{2}-a} \tag{34}$$

When $\frac{b}{2} > a$, then the marginal costs are increasing in firm productivity. In equilibrium more productivity firms have higher revenue and are larger. Therefore, we expect a positive correlation between marginal costs and firm size. Combining this with the prediction that markups are increasing in firm size, produces the combined positive relation of firm size with marginal costs and markups. While we do not directly observe quality q_j^*, the fact that model produces consistent relation between the observable of firm size and estimated marginal costs and markups suggests that the hypothesized quality channel seems to right underlying framework. I now analyze the implications of this model for how markups should vary over time in response to demand shocks to the poor. Testing this prediction in the data provides additional evidence in support of this theoretical framework.

G Alternative Demand System: Explicitly Additive Preferences

In this section, I consider an alternate demand system with explicitly additive preferences. On the consumer side, consumer have directly explicitly additive preferences (Generalized Stone-Geary preferences) and have heterogeneous quality valuations. Specifically, when faced with identical prices, rich and poor households allocate their consumption expenditure differently across the quality ladder. The production side again follows Kugler and Verhoogen (2011) and features endogenous input and output quality choice across heterogeneous firms.

There are I consumer groups, and a finite number of exogenously given heterogeneous firms. Consumers are indexed by i, sectors by s and firms by j.

A. Demand

Consumer i has Stone-Geary preferences over the consumption goods x_{ij}

$$U_i = \sum_j \left[q_j^{\phi_i} \left(x_{ij} - \underline{x}_{ij} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

where q_j is the product quality; x_{ij} is consumption and; ϕ_i captures the consumer's valuation of quality, which I assume is strictly increasing in the income level z_i, which I take as exogenous.

The price elasticity of demand for consumer i demand for product j is given by

$$\sigma_{ij} \equiv -\frac{p_j}{x_{ij}} \frac{dx_{ij}}{dp_j} = \sigma \left(1 - \frac{\underline{x}_{ij}}{x_{ij}} \right) \left(1 + \frac{p_j \underline{x}_{ij}}{z_i - \sum_i p_j \underline{x}_{ij}} \right) \tag{35}$$

Therefore, the price elasticity of consumer is decreasing with the amount of residual income. A direct implication is that wealthier households have lower price elasticity of demand. In this setting, the price elasticity of demand for firm i is the *sales-weighted* average of price elasticity of demand of its consumer base:

$$\tilde{\sigma}_j = \sum_i \sigma_{ij} \psi_{ij} \tag{36}$$

The greater the firm's share of sales made to a particular income group (ψ_{ij}), the higher is the weight places on that group's price elasticity of demand (σ_{ij}). Recall that, as per assortative matching, wealthier households have a tendency to consume more from larger firms. Since σ_{ij} is lower for wealthier households, firms that make larger share of sales to wealthier households (i.e. larger firms) face lower elasticity of demand.

H Demand composition channel under a general framework

This section provides a general framework for understanding the role of changes in demand composition for price and markup cyclicality. This framework has the advantage that it does not rely on assortative matching. The objective is to document the role of demand composition independent of the product quality channel. Consider N identical firms in imperfectly competitive economy. Total quantity demanded is Q and each firm produces q which implies $Q = Nq$. Each firm faces cost $c(q)$ (and thus marginal costs $c'(q)$). The elasticity of demand is $\varepsilon = -\frac{d\log Q}{d\log P}$.

The quantity demanded is given by $Q = f(P;Z)$, where Z is an exogenous demand shifter orthogonal to prices such that $\frac{dQ}{dZ} > 0$. Firms maximize over quantities after taking the residual demand curve as given:

$$\max_{q} \quad P(Q)q - c(q)$$

The first order condition is $P'(Q)q + P(Q) = c'(q)$. Rearranging and substituting for price-elasticity of demand gives us $P = \left(\frac{N\varepsilon}{N\varepsilon-1}\right) c'(q)$. The first term in the brackets is the firm's markup over marginal costs. Notice that the above expression hold for any general function of cost function $c(.)$. The price responses to exogenous demand shifter Z, can be decompose in markup and marginal costs responses based on the following expression:

$$\frac{dP}{dZ} = \underbrace{\frac{-N}{(N\varepsilon-1)^2}\left(\frac{d\varepsilon}{dZ}\right)}_{d\text{Markups}} c'(q) \tag{37}$$

where $c'(q)$ is the marginal cost. Thus, the price-effect of demand shift depends on how aggregate price-elasticity changes in response to the demand shifter Z. For example if the demand shifter have multiplicative effect i.e. $Q = ZP^{-\beta}$, then elasticity of demand (equal to β here) and is independent of Z. On the other hand, if the aggregate price-elasticity of demand increases when the market size increases, then prices (and markups) will decrease. In presence of heterogeneous consumers, the aggregate elasticity in the economy is $\varepsilon = \frac{Q_1\varepsilon_1 + Q_2\varepsilon_2}{Q}$. We are interested in understanding how aggregate price-elasticity changes with respect to demand shifter Z:

$$\frac{d\varepsilon}{dZ} = \frac{1}{Q^2}\left[\left(\frac{dQ_1}{dZ}\varepsilon_1 + \frac{dQ_2}{dZ}\varepsilon_2\right)(Q_1+Q_2) - \left(\frac{dQ_1}{dZ} + \frac{dQ_2}{dZ}\right)(Q_1\varepsilon_1 + Q_2\varepsilon_2)\right]$$

Rearranging this provides us with the following expression:

$$\frac{d\varepsilon}{dZ} = (\varepsilon_1 - \varepsilon_2)\frac{Q_1Q_2}{Q^2}\left[\frac{d\log Q_1}{dZ} - \frac{d\log Q_2}{dZ}\right]$$

Thus the change in aggregate price-elasticity to demand shocks depends on (i) differential price elasticity across consumers i.e. $(\varepsilon_1 - \varepsilon_2)$ (ii) how demand changes *relative* demand from the two consumer segments i.e. $\left[\frac{d\log(Q_1/Q_2)}{dZ}\right]$.

$$\frac{d\varepsilon}{dZ} = (\varepsilon_1 - \varepsilon_2)\frac{Q_1Q_2}{Q^2}\underbrace{\left[\frac{d\log(Q_1/Q_2)}{dQ}\right]}_{\text{Composition effect}}\frac{dQ}{dZ} \tag{38}$$

This implies that aggregrate elasticity (hence markups) depends on how higher aggregate demand changes the composition of demand i.e. $\left[sign(\varepsilon_1 - \varepsilon_2).\frac{d\log(Q_1/Q_2)}{dQ}\right]$. The intuition is straightforward: if higher demand is due to an increase in market size from more-price sensitive population the aggregate price-elasticity faced by firms increases. This puts downward pressure on prices and markups. The empirical results in the paper are consistent with this hypothesis: higher rainfall increases and drought decreases the market share of price-sensitive population *within* a district. Prices and markups for consumer goods increase (decrease) in years when share of price-sensitive consumers increases (decrease) in market size. This simple model generates few rich predictions that can be empirically tested.

Proposition 3. *Average price-elasticity increases when an increase in market size also increases demand from more price-sensitive consumers.*

Proof: Let consumer segment 1 be more price-sensitive than segment 2 ($\varepsilon_1 > \varepsilon_2$). If $\frac{d\log(Q_1)}{dQ} > \frac{d\log(Q_2)}{dQ}$, then $\frac{d\varepsilon}{dZ} > 0$ (as $\frac{dQ}{dZ} > 0$).

When demand shifter Z increases the demand of consumers with higher price-sensitivity more than consumers with lower price-sensitivity, the *aggregate* price-elasticity faced by firms that cater to both these consumers increases. In response, those firms lower their prices and markups. Notice that demand shifter Z does not effect the average price elasticity for firms that only cater to a homogeneous consumer base ($\varepsilon_1 = \varepsilon_2$). For these firms, the prices and hence price elasticity does not change with respect to demand shifter Z.

Proposition 4. *Prices and markups decrease if higher market size increases relative demand from price-sensitive consumers.*

Proof: This follows directly from Proposition (1). As $\frac{dP}{dZ} = \frac{-N}{(N\varepsilon-1)^2}\left(\frac{d\varepsilon}{dZ}\right)c'(q)$, prices move inversely with aggregate price-elasticity. Thus, prices *decrease (increase)* in response to demand shifter Z if aggregate price-elasticity ε faced by firm *increases (decreases)*. Moreover, change in demand composition has no effect on firms with $Q_1 = 0$ or for $Q_2 = 0$. When mapping this to data, this implies that firms in lowest size quintile (those selling only to poor households) and firms in highest size quintile (those selling only to the rich households) should not change their prices and markups in response to demand shocks.

Proposition 5. *When demand from price-sensitive consumers increases, prices and markups decrease less in more competitive consumer markets.*

Proof: From equation (37) : $\frac{d^2P}{dZdN} = \frac{d\varepsilon}{dZ}\frac{(N\varepsilon+1)}{(N\varepsilon-1)^3}c'(q)$. Thus $\frac{d^2P}{dNdZ} > 0$ if $\frac{d\varepsilon}{dZ} > 0$. With higher competition, prices decrease less in response to changes in demand that increases aggregate price-elasticity.

Under the extreme case of perfect competition, firms are price-takers: they have less market power in exerting markups and set prices equal to marginal costs. Thus, markups are not responsive to demand shocks.

A few assumptions made above deserves discussion. First, I have assumed that the price-elasticities ε_i's for individual consumer groups i does not change with respect to the shock Z. This assumption is well justified if Z is a temporary shock — the temporary shocks effect the quantities Q_i demanded by the consumers with little to no change to their long-run elasticity of substitution ε_i. Second, the demand shifter Z are orthogonal to prices and firm's supply curve. If Z affects the prices directly instead of through quantities demanded, then any effort to understand price responses to demand would suffer from reverse causality. If Z effects firm's supply curve, then any prices changes in response to Z would be driven by changes to marginal costs rather than changes to markups (an omitted variable concern).

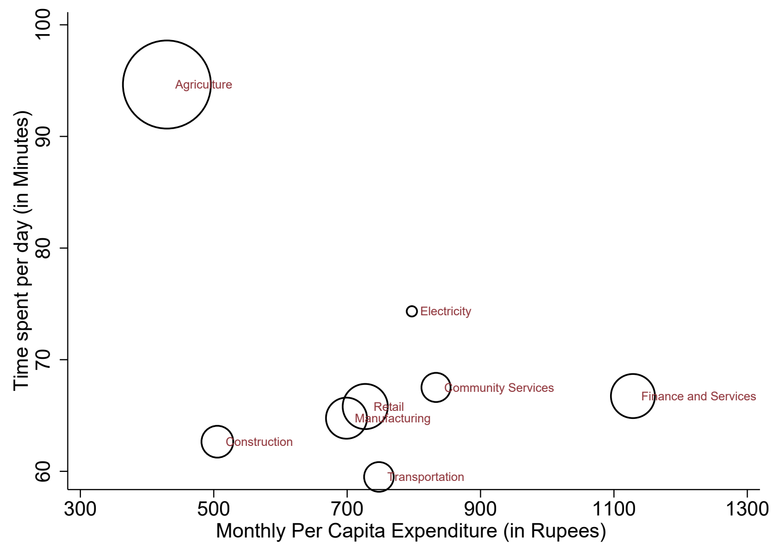
I Consumer Demand Heterogeneity: Additional evidence from shopping behavior

In this section, I provide additional empirical evidence in support of poor differing in their product market behaviour compared to the rich. Consumers' shopping behaviour such as shopping intensity has been used as close proxy for price elasticities of consumers (Lach (2007)). I present evidence in support for higher shopping intensity of rural population in the Time Use Survey that reports time allocation across 6,000 households across various occupations in 1999. The survey asks for time allocation by household members across various work-related and household-related tasks on the previous day of the survey. It also asks information on the district and (anonymized) village place of residence, total expenditure incurred by the households in the previous month, the age and sex of the household and number of members in the household. I use the information under the field "Time spent on shopping for goods and non-personal services". More importantly for this analysis, this field excludes travel time associated with household shopping, which is asked separately in the survey.

As seen in Figure I.11, time spend on shopping activities per day averages 90 minutes for population employed in agriculture and approximately 60 minutes for the rest of the population. At the same time, the monthly per household member consumption expenditure is the lowest whereas the share among total population is the highest for agricultural sector (49% percent of the population is employed in agricultural sector). However, it could still be the case that the above relationship is driven by different household and location characteristics. Table I.15 performs an OLS regression of time shopping based on household income after controlling for confounding characteristics. Column (1) shows that poorest population spends 10 minutes more time shopping relative to the median population and that this effect persist one I control for travel time (Column (2)). Column (3) and (4) shows that similar pattern holds for population employed in the agricultural sector.

While shopping time is not the perfect measure to capture time spent searching for lower prices, it is certainly one of the ideal ones closest to the concept. These patterns, along with the estimates of price elasticities documented in Section III, strengthen the hypothesis that poor households are more demand elastic than the wealthier households.

Figure I.11: Time Spent on Shopping across Income groups



Notes: This plot shows the per capita time spent on shopping per household against their monthly per capita expenditure by industry. 366 NIC 3-digit sectors are collapsed to 9 NIC 2-digit industries. The size of the bubble represents the share of population employed in NIC 2-digit industries using 1999 NSS employment data.

Table I.15: Time spent on shopping by income groups

	Shopping Time			
	(1)	(2)	(3)	(4)
1(employed in agricultural sector)			6.371**	6.353*
			(2.609)	(2.977)
Poorest Quintile (Relative to Median)	10.693**	5.984**		
	(4.454)	(2.791)		
2nd poorest Quintile (Relative to Median)	2.276	0.362		
	(1.433)	(1.724)		
2nd richest Quintile (Relative to Median)	0.694	1.790		
	(3.703)	(2.540)		
Richest Quintile (Relative to Median)	3.425	3.033		
	(2.861)	(2.352)		
Travel Time		0.464***		0.444***
		(0.037)		(0.036)
Observations	5,609	5,609	5,609	5,609
R-squared	0.485	0.584	0.487	0.601
Village/town f.e.	✓	✓	✓	✓
Household Controls	✓	✓	✓	✓

Notes: The analysis here based on Time Use Survey data (1998-1999) and shows that poorest income group (and households employed in agricultural sector) spend more time per shopping trip. This is suggestive that either search cost in shopping is lower for this population or they spend more time shopping as they are more price-sensitive. All regression include village/town fixed-effect and household controls. Household controls include age for head of household, gender of head of households, number of members in household. Data is from Time Use Survey. Standard errors clustered at district level are reported in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.