Do Clouds have a Silicon Lining for Firms? Contract Hiring and Computer Investment: Evidence from Rainfall Shocks

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Abstract

How do firms' hiring and firing decisions for contract workers change due to computer capital investment? We consider district-level rainfall shocks as exogenous industrial labour demand shocks. Using Indian firm-level data from 2000 to 2010, we look at how firms change hiring decisions due to change in computer capital, in the face of rainfall shocks. We find firms with a greater than average share of computer capital, is associated with a decline in hiring or firing by 2.32, in the face of demand shocks. Our results are robust to a set of alternative measures such as computer capital share in expenditure, dummies for above-median computer capital share, above-industry average computer capital share, among others. We also find that the results are mainly driven by contract workers involved in the main production process (and not for workers carrying out peripheral activities). We conclude that firms investing relatively more in computer capital reduce the number of contract workers hired when exposed to positive demand shocks, suggesting labour-saving impact of technology at play.

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1 Introduction

The role of technology in driving labour market changes has been well established in the literature.[1]The literature provides mixed evidence on whether technology adoption leads to a rise or fall in employment. Firm-level studies have documented that technology adoption leads to both decreases in employment (Autor et al. (1998), Autor and Salomons (2018), Bessen et al. (2019), Acemoglu and Restrepo (2020)), as well as increases in employment (Van Reenen (1997), Blanchflower and Burgess (1998), Bessen (2019), Aghion et al. (2020)). Studying how technology affects hiring decisions is a difficult exercise. Technology is not an exogenous or random shock as the decision to invest in technology is taken by firms. Our study proposes a way to overcome this issue by analyzing how firms with different levels of computer capital expenditure respond differently to exogenous demand shocks. We examine a panel of Indian manufacturing firms for the period 2000-2010 and analyze if hiring decisions in response to exogenous transitory demand shocks vary due to different levels of computer capital expenditure. We use lagged rainfall shocks to proxy for transitory demand shocks experienced by firms (Adhvaryu et al. (2013), Chaurey (2015)). Firm decisions do not affect the occurrence of rainfall shocks, hence demand shocks arising from rainfall shocks are exogenous.

This paper addresses the following question: Do firms that invest more in computer capital (and hence invest more in computer-aided technology), hire workers differentially in response to transitory demand shocks? Computer capital investment is not an exogenous

[1]Tinbergen (1974, 1975) linked technology to the relative demand for skills, providing a precursor to the literature on SBTC or skill-biased technological change (Katz and Murphy (1992)). SBTC categorizes workers into high and low skill groups and explores whether improvements in technology increase the demand for high-skilled workers relative to low-skilled workers. The task-based framework (Autor et al. (2003)) describes how machines displaces workers from occupations based on the types of tasks or activities carried out in jobs. Acemoglu and Autor (2011) show how workers are displaced from manufacturing, sales and clerical occupations, given the type of activities or tasks that workers carry out in these occupations.

variable. It is difficult to obtain computer capital investment "shocks" or consider computer capital spending as random across firms, as firms decide how much to invest in computer capital. We create a computer capital share dummy for firms that have above-average computer capital expenditure. Identification comes from the interaction of computer capital share dummy and exogenous demand shocks (Nizalova and Murtazashvili (2016)). For robustness, we also construct a host of alternative measures reflecting computer capital investment and check if we obtain similar results.

For measuring exogenous demand shocks, we use data on rainfall shocks following Adhvaryu et al. (2013) and Chaurey (2015) who show that industrial labour demand is sensitive to rainfall fluctuations through weather impact on agricultural productivity. Positive rainfall shocks have a positive impact on agricultural production and agricultural productivity which leads to relatively higher income and higher spending for agricultural workers. Increase in spending suggests an increase in demand for industrial goods. As more production takes place following rainfall shocks, there is a consequent increase in demand for workers in the industrial sector. Thus, rainfall shocks translate to demand shocks for firms.[2] Rainfall shocks are exogenous as firm decisions or unobserved labour market changes will not affect rainfall fluctuations. Hence, the demand shock arising from a rainfall shock is also exogenous to a firm's decisions. When faced with these exogenous transitory demand shocks, firms lay-off or hire more workers to cater to the changes in demand.

We find that firms with above-average computer capital share tend to hire 2.32 fewer contract workers compared to firms with lower-than-average computer capital share, in response to positive transitory demand shocks. This differential hiring is 11.33% of the

[2] Adhvaryu et al. (2013) and Chaurey (2015) show that positive rainfall shocks lead to an increase in monthly per capita expenditure implying an increase in spending. Chaurey (2015) also shows that both industrial wages and employment increase following rainfall shocks for the period 2000-2010, which are sufficient conditions to conclude a net increase in demand for industrial workers, even if there are supply shocks due to rainfall. We discuss this in detail in Section 3.

sample mean of contract employment. Our results are robust to using a number of alternative measures of computer capital expenditure. We find that a 10 percentage point increase in computer capital expenditure share leads to a reduction in average contract hiring by 2.8 workers in the face of demand shocks. Firms with computer capital share above the sample median computer capital share reduce contract hiring by 1.7 workers. Our results are also robust to other measures that consider industry and state-industry average computer capital shares. We also confirm that the reduction in hiring is for contract workers who carry out activities directly involved in the manufacturing process and not for activities in peripheral works such as security, cleaning services, etc.

As we are looking at how hiring decisions of firms are affected in the face of rainfall shocks or transitory demand shocks, one may be concerned that labour regulations will protect workers from being laid off in the face of such transitory shocks. The Industrial Disputes Act, 1947 (IDA) is the primary labour regulation in India that restricts firms from laying off workers. However, the IDA does not cover contract workers. Contract workers are temporary workers who are paid for less than 240 days in any 365 days period.[3] Chaurey (2015) finds that firms in states with strict labour regulations tend to hire contract workers in response to transitory shocks and no significant hiring of regular workers is observed following these same shocks. For this reason, we focus on contract workers and analyze how firms' hiring of contract workers vary by computer capital share.

We add to the literature that examines whether technology increases or decreases employment. Empirical studies have found evidence of workers being displaced from automating firms (Autor and Salomons (2018), Bessen et al. (2019), Acemoglu and Restrepo (2020))

[3] A provision for protection of contract workers exist in the Contract Labor Act (1970) which grants state the authority to ban use of contract labour in any establishment, and makes provisions for proper disbursement and prevent wage payment delays. But it has been found that enforcement of these regulations is weak (Bhandari and Heshmati (2008), Basu et al. (2021)).

and declining employment in manufacturing jobs due to computer technology (Autor et al. (1998), Vashisht (2018)). Machines carry out the work of human labour, essentially causing a labour substitution effect. There is also evidence of technology increasing demand for workers (Blanchflower and Burgess (1998), Bessen (2019), Hjort and Poulsen (2019), Aghion et al. (2020)). Automation can help to reduce production costs and hence prices which leads to an increase in demand for goods, thereby resulting in an increase in production and a consequent increase in demand for labour. Our work is closely related to the recent research that employs quasi-experimental variation to study the relationship between technology and employment. Bessen et al. (2019) studies the impact of automation on employment and circumvents endogeneity issues by reporting firm's employment before and after automation investment spikes. However, this restricts the sample to firms which have made significantly large investments in automation. Aghion et al. (2020) uses a shift-share IV (Instrumental Variable) and estimate employment before and after automation expenditure. However, the analysis is restricted to the subset of firms that imports automation inputs. In our analysis, we look at how firms' hiring decisions vary by computer capital investment in the face of exogenous shocks. Irrespective of the size of computer capital investment or importing decisions, the demand shock is experienced by all firms in our sample. Thus, our strategy has the advantage of not restricting the sample to importing firms or to firms with large investments in technology.

Our study adds to other strands of literature. As our study looks at how heterogeneity in computer capital investment across firms affects hiring decisions in response to demand shocks, we add to studies that focus on firm heterogeneity due to technology. Doms et al. (1995) is one of the first studies that stress on controlling for producer heterogeneity arising from differences in types and level of capital investments. The outcome of interest for the study is firm entry, exit and growth. Yeaple (2005) develops a theoretical model where some firms choose to adopt new technologies whereas others do not. Firms with new (low cost) technologies are then able to produce more and enter the export market. Thus, heterogeneity in technology adoption leads some firms to become exporters while others remain non-exporters. Aboal et al. (2015) investigate the effect of product and process innovation on employment growth and additionally explores the presence of heterogeneous effects of innovation.[4] They find differential effects of innovation on employment across these technologically diverse sub-sectors. Similar to our study, this study highlights the importance of heterogeneous effects on employment arising due to different expenditure on innovation. However, our question is different as we are examining employment decisions in response to exogenous demand shocks.

We also add to the literature which analyzes impact of weather on economic outcomes (Dell et al. (2014)).[5] Studies focusing on the manufacturing sector find that high temperatures have a negative impact on industrial output (Zhang et al. (2018), Somanathan et al. (2021)). Hsiang (2010) records relatively higher output losses in the non-agricultural sector than the agricultural sector due to temperature changes from tropical cyclones. In our study, we focus on how firms are prone to demand shocks due to changes in agriculture productivity from weather fluctuations. Firms respond to demand shocks arising from rainfall shocks by changing output and employment, as discussed earlier. Hence, any impact on hiring decisions arising from heterogeneous computer capital investment during such weather-driven demand shocks becomes important.

The paper is organized as follows. In the next section we discuss the sources of data and how we measure rainfall shocks and computer investment for Indian firms. In Section 3

[4] Their study analyzes the differences among high-tech and low-tech sub-sectors (high innovation expenditure and low innovation expenditure as share of turnover, respectively). The study points out that these sub-sectors have very different demand profiles for workers leading to dissimilar workforce composition.

[5] Dell et al. (2014) discuss studies that have analyzed the effects of weather variation on industrial output (Hsiang (2010), Jones and Olken (2010), Dell et al. (2012)).

we discuss the empirical strategy in detail. Section 4 discusses results on how computer capital investment affects hiring decisions during demand shocks and carries out robustness checks. Finally, Section 5 concludes.

2 Data

We use data from several sources for our analysis. We use the Annual Survey of Industries (ASI) of India to obtain firm-level capital expenditure and employment data from 1999-2000 to 2009-2010 for firms in the manufacturing sector.[6] The reference year for the ASI is the accounting financial year from 1st April to 31st March of the following year. All registered industrial units in India, which employ at least 10 workers and use electricity, or employ at least 20 workers but do not use electricity, are covered by the ASI.[7]

ASI surveys provide firm-level annual data such as expenditure on assets and liabilities, employment, labour cost, receipts, expenses, input items (indigenous and imported), cost and quantity of output produced, etc. We use data on the number of contract workers a firm hires each year. The ASI data also includes information on man-days (the number

[6] As mentioned above, Chaurey (2015) shows that there is no statistically significant impact of rainfall shock on agricultural wages, but there exists statistically significant positive impacts on industrial wages and monthly per capita expenditure for the period 2000-2010. These findings point to rainfall shocks acting as exogenous labour demand shocks for the industrial sector. We restrict out study to this period as we leverage rainfall shocks as exogenous labour demand shocks in our analysis. This period is also relevant given that the key indicator of technology in our study is computer capital. The 2008 KPMG report (IBEF (2008)) points out that demand for Computer Numerical Control machines (the production machines that require computer capital) have outgrown conventional tools from the early 2000s. The demand for these tools largely arises from the manufacturing sector. Erumban and Das (2020) also document a significant increase in ICT investment for this period in India.

[7] The ASI frame consists of a census sector (units surveyed every year) and a sample sector (sampled every few years). The census sector covers all firms in five industrially backward states (Manipur, Meghalaya, Nagaland, Tripura and Andaman and Nicobar Islands) and large factories for the rest of the country. The ASI definition of large factory underwent a change. From ASI 2001 onwards, a large factory to be covered in the census sector is defined as an industrial unit with 100 or more employees, whereas for years before 2001 the ASI definition of a large factory consists of an unit with 200 or more workers. The firms not covered in the census sector constitute the sampling frame for the sample sector. A third of these firms are randomly selected in the survey each year.

of workers employed on each day summed over all days in a year) separately for manufacturing and non-manufacturing work. Manufacturing work refers to activities in the main or core production process whereas non-manufacturing work refers to peripheral activities of the production process like repair, maintenance, etc. ASI reports the yearly gross value of computer equipment and software for each firm. We also obtain measures for the total capital value for each firm which includes buildings, plant and machinery, transport equipment, computer equipment including software, and other capital equipment.

We also use the US measures of computer capital share in constructing an alternative measure for our study. We obtain the US industry-wise computer capital expenditure and total capital expenditure for the period 2002-2010 from the Annual Survey of Manufactures (ASM). ASM provides industry-level estimates of key statistics for manufacturing sector[8] establishments with one or more paid employees. It provides measures of US manufacturing activity, products, and location for the public and private sectors. The survey provides yearly data on employment, payroll, hours, cost of materials, receipts, value added, capital expenditures, etc. at the industry level.

For our main analysis, we use monthly rainfall data from the Center for Climatic Research, University of Delaware, which is available from 1900 to 2017, at 0.5 degree by 0.5 degree latitude-longitude grid.[9] We match annual rainfall (in mm) to the latitude and longitude nearest to the geographic centroid of each district using district shapefiles.[10]

[8]Industries are classified according to North American Industrial Classification Standard (NAICS). We match the 3-digit level NAICS to the 2-digit level Indian National Industrial Classification (NIC) in our study.

[9]The Delaware rainfall data is available after spatial interpolation was carried out with the spherical version of Shepard's algorithm, which employs an enhanced distance-weighting method (Shepard (1968), Willmott et al. (1985), Willmott and Matsuura (2018)).

[10]Shapefiles store geographic data such as location, shape and attributes of geographic features in a vector format. Geographic features in a shapefile can be represented by points, lines, or polygon areas which allows one to run analyses with geographic data such as constructing the centroid of a geographic location.

We define the exogenous demand shock from rainfall data following Jayachandran (2006), Adhvaryu et al. (2013), Chaurey (2015) and Kaur (2019). Exogenous demand shock is a rainfall shock in district d in year t, given by:

$$Rainshock_{dt} = \begin{cases} 1, & \text{if rainfall in district } d \text{ in year } t \text{ is above the 80th percentile,} \\ 0, & \text{if rainfall in district } d \text{ in year } t \text{ is between the 20th and 80th} \\ & \text{percentiles,} \\ -1, & \text{if rainfall in district } d \text{ in year } t \text{ is below the 20th percentile,} \end{cases} \tag{1}$$

where the percentiles correspond to the the rainfall distribution for district d for the period 1998-2008. Similar to Chaurey (2015), we look at lagged effect of rainfall. We construct rainfall shock from rainfall measures in the previous calendar year. For example, to correspond to the ASI accounting year from 1st April 2004 to 31st March 2005, rainfall measures are from January 2003 to December 2003. This allows us to account for the time that firms may take to respond to demand shocks arising from the effects of rainfall on the local economy.

Table 1 reports the summary statistics of employment and computer capital expenditure data in our sample. On an average, 20.47 contract workers are employed in a firm, compared to 47.55 regular (or permanent) workers. Thus, employment in firms is largely regular. But, at the same time, contract workers employment is also non-trivial, consisting of around 18.96% of total workforce. Contract workers are mainly involved in the core manufacturing activities of the production process, whereas contract non-manufacturing man-days for peripheral works is very low, on average. The share of computer capital in total capital for a firm is 2.88% on average in our sample. In Table 1 we report separately the summary statistics for firms with computer capital share greater than 2.88% (or above-average computer capital share) in column 2 and firms with computer capital share less than or equal to 2.88% (or below-average computer capital share) in column 3. On an average, firms with above-average computer capital share employ relatively fewer workers (both regular as well as contract) and have a lower total capital value compared to firms with below-average computer capital share. The share of observations in our sample experiencing negative rainfall shocks (16%) is similar to the share of observations receiving positive rainfall shocks (20%). We also find that the share of observations receiving positive and negative rainfall shocks are similar for firms with above-average or below-average computer capital share. In Figure 1 we demonstrate that the industry distribution also is similar across positive and negative rainfall shocks in our sample. Thus, there should not be any concern that specific industries are facing only one type of rainfall shock in our sample.

3 Empirical strategy

Rainfall shocks are exogenous to a firm's decisions – it is unlikely that a particular firm's decision will affect the weather. Hence, the demand shock arising from the rainfall shock is also exogenous to a firm's hiring decisions. Good rainfall (or positive rainfall shocks) will lead to higher agricultural income or monthly per capita expenditure, leading to a larger demand for industrial goods and hence for industrial labour (a labour demand shock). On the other hand, good rainfall might also lead to a higher demand for agricultural labor, thus resulting in a labour supply shock for industrial sector firms. Thus, whether rainfall shocks represent a demand shock or a supply shock for firms depends on whether the demand shock dominates the supply shock. A sufficient condition for demand shock to dominate the supply shock is to observe that, in equilibrium, both industrial wages and employment increase.[11] Figures 2 and 3 illustrate this point.

In both the figures, labour demand curve shifts to the right, from DD to $D'D'$, representing the labour demand shock. Figure 2 illustrates the positive labour supply shock – supply curve shifts to the right from SS to $S'S'$, while Figure 3 demonstrates the negative labour supply shock – supply curve shifts to the left from SS to $S'S'$. In Figure 2, since both the demand and supply curves shift to the right, equilibrium employment will definitely increase. Whether equilibrium wages will also increase depends on the relative sizes of the shifts. If the shift of the labour supply curve is lower than the shift of the labour demand curve (distance y between SS and $S'S'$ is less than distance x between DD and $D'D'$), equilibrium wages increase. On the other hand, if the shift of the labour supply curve exceeds the shift of the labour demand curve (distance $x + e$ between SS and $S''S''$ is more than distance x between DD and $D'D'$), equilibrium wages decrease. Clearly, the only way both equilibrium wages and employment can increase is when demand shock dominates the supply shock. In Figure 3, since demand increases while supply decreases, equilibrium wages will definitely increase. What happens to equilibrium employment, on the other hand, depends on the relative sizes of the demand and supply shocks. Following a similar analysis as above here also we can conclude that both equilibrium wages and employment can increase only when demand shock dominates the supply shock.

Chaurey (2015) shows that both industrial wages and employment rise for the period 2000-2010 in response to positive rainfall shocks (the converse holds for negative rainfall

[11] Chaurey (2015) discusses three possible scenarios on the supply side. In the first case, no agricultural worker may move to the industry, resulting in a rise in industrial wages and employment owing to the larger demand for industrial labour. The second case is when agricultural workers move to the industry. In this case, as long as demand exceeds the supply of workers in the industry, there will be an increase in both industrial wages and employment. In the third case, rainfall attracts labour from industries to agriculture so that the industries face a negative supply shock. However, if the industrial wages and employment have increased, then the increase in labour demand must be greater than the decrease in labour supply.

shocks).[12] Thus, he establishes that rainfall shocks do represent a demand shock for the industrial sector in India for the period 2000-2010. Therefore, for our study, we consider rainfall shocks as exogenous transitory demand shocks for firms.

We analyze how a firm's contract employment varies by computer capital expenditure interacted with whether the district (in which the firm is located) has experienced a demand shock. As a measure of a firm's computer capital expenditure, we construct a dummy ($Compdum_{idt}$) that takes value 1 when the computer capital expenditure share of firm i in district d in year t is above the mean of the sample (2.88%), and 0 otherwise. We run the following regression:

$$\begin{aligned} Contract_{idt} = \gamma_t + \delta_i + \lambda_{kt} + \beta_1 Rainshock_{dt-1} + \beta_2 Compdum_{idt} \\ + \beta_3 Rainshock_{dt-1} * Compdum_{idt} + \epsilon_{idt}, \end{aligned} \tag{2}$$

where $Contract_{idt}$ measures the contract employment of firm i in district d in year t. The variable $Rainshock_{dt-1}$ refers to lagged rainfall shock which proxies for transitory demand shock. We include year fixed effects, γ_t, to control for macroeconomic year-specific events in our regressions. We also include firm fixed effects, δ_i, to control for time-invariant firm characteristics. Industry-year fixed effects, λ_{kt}, control for unobserved time-varying factors in an industry (such as changes in tariffs or regulations) which may affect both employment and computer capital investment in an industry.[13] We cluster standard errors at the district-level given that the rainfall shock is measured at the district-level. The impact of

[12]Both industrial wages and monthly per capita expenditure rise for the period 2000-2010 following positive rainfall shocks. The positive impact of rainfall shock on monthly per capita expenditure signifies an increase in spending, and possibly an increase in demand for industrial goods. There is no statistically significant impact of rainfall shocks on agricultural wages for the same period. He shows that industrial employment increases (decreases) in response to positive (negative) rainfall shocks for a subset of the period (1999-2008), confirming that there is, in net, a demand shock for firms when rainfall shocks occur.

[13]Firms are classified into industries according to the National Industrial Classification (NIC). Description of industries is provided in Appendix A.1.

lagged rainfall shock on contract employment is captured by β_1. The coefficient β_2 captures the effects of above-average computer capital expenditure on contract employment. Our coefficient of interest β_3 captures the differential effect on contract hiring in response to demand shocks for firms that have above-average computer capital share as compared to firms that have lower-than-average computer capital share.

In an ideal setting, if computer capital expenditure was randomly assigned to each firm then one could easily regress employment on computer capital to obtain causal estimates. However, in reality, the number of workers to hire and how much to invest in computers are both decisions taken by the firm. It is possible that workers may choose to leave when they anticipate that a firm will invest in an automation technology. Alternatively, a firm may start hiring workers who have computer-based skills in anticipation of increased computer capital expenditure. Also, unobserved labour market conditions may affect both computer capital investment and employment leading to endogeneity issues. Thus, simply regressing contract employment on computer capital share will not capture the hiring decisions taken by a firm due to computer capital investment.

In this study, identification comes from the interaction of computer capital dummy and rainfall shocks. Interaction of an endogenous variable (computer capital expenditure) with an exogenous variable (rainfall shock) is exogenous under mild assumptions (Nizalova and Murtazashvili (2016)). In equation 2, β_3 gives us causal estimates.

We also check with a host of alternative measures such as computer capital share, a dummy for computer capital share above the median computer capital share, a dummy for computer capital share above the industrial average and a dummy for computer capital share above the average computer capital share in a state in an industry. We also consider variables that classify firms based on the computer capital share in the first sampling year of a firm. As a further check, we construct a dummy based on computer capital shares in a year in industries in the US for the period 2002-2010.

4 Results

4.1 Main Results

We document the relationship between firm-level contract employment and firm-level computer capital expenditure share in response to rainfall shocks. Table 2 presents the results of regressing contract employment on rainfall shocks and rainfall shocks interacted with the measure of firms with above-average computer capital share, as specified in equation (2). Column 1 runs the regression equation (2) with firm fixed effects and year fixed effects. Column 2 presents our preferred specification with firm and year fixed effects, as well as industry-year fixed effects. We find that the coefficient for rainfall shock is statistically significant and positive: positive (negative) rainfall shocks increase (decrease) contract employment, which is in line with previous literature (Adhvaryu et al. (2013), Chaurey (2015)). Following positive rainfall shocks, firms face a positive demand shock and on average hire 1.31 more contract workers. As discussed above, $compdum_{idt}$ takes the value 1 if computer share is above-average (above 2.88%) and 0 otherwise. The interaction term, computer capital dummy interacted with rainfall shock, is statistically significant and negative. Firms on average hire more contract workers in response to a positive demand shock. The negative coefficient on the interaction term implies that compared to firms with lower-than-average computer capital share, firms with above-average computer capital share hire fewer contract workers following positive rainfall shocks. We find that a firm with above-average computer capital share hires 2.32 fewer contract workers compared to firms with lower-than-average computer capital share, in response to a positive rainfall shock. This differential hiring amounts to 11.33% of the sample mean of contract employment (20.47).

Table 3 presents our regression results separately on rural firms (firms located in the rural sector) and urban firms (firms located in the urban sector). Rainfall shock leads to a statistically significant increase in contract hiring for rural firms whereas there is no statistically significant impact on contract hiring for urban firms. It is not surprising that the impact will be stronger for rural firms since the mechanism of a rainfall shock translating to a demand shock for the industrial sector is through changes in income and spending from the agricultural sector.[14] The coefficient on the interaction term is statistically significant and negative for rural firms: firms with above-average computer capital share hires 4.74 fewer contract workers compared to firms with below-average computer capital share in the face of demand shocks. For urban firms, however, we do not find any statistically significant impact.

We also check our results separately for positive rainfall shocks and negative rainfall shocks. For this exercise, positive rainfall shock takes value 1 if rainfall in district d in year t is above the 80^{th} percentile of rainfall distribution, and 0 otherwise, while negative rainfall shock takes value 1 if rainfall in district d in year t is below the 20^{th} percentile of rainfall distribution, and 0 otherwise. The regression results are reported in Table 4. In column 1 we observe that firms with above-average computer capital share tend to hire 2.62 fewer contract workers compared to firms with less-than-average computer capital share in response to a positive demand shock. Note that in case of negative rainfall shocks, firms on average tend to layoff contract workers as seen from the statistically significant and negative coefficient of 1.93 in column 2. The interaction term has a statistically significant and positive

[14]This result is similar to the findings in Chaurey (2015). He finds a statistically significant impact of rainfall on rural firm employment but no statistically significant impact on urban firm employment. This provides further support that rainfall shocks are demand shocks arising due to the impact of rainfall on the agricultural sector.

coefficient of 2.86. As firms on average lay-off workers during negative demand shocks, the positive coefficient on the interaction term implies that firms with relatively above-average computer capital share tend to lay off fewer contract workers following negative demand shocks, compared to firms with less-than-average computer capital share.

We also check how contract hiring differs between machinery production industries and non-machinery production industries.[15] In Table 5 we report results of our main regression for contract workers employed in non-machinery industries in column 1 and contract workers employed in machinery industries in column 2. It is interesting to note that the coefficient of the interaction term is negative and statistically significant for machinery industry contract workers (and not statistically significant for non-machinery industry contract workers). Machinery industries with above-average computer capital investment hire 4.02 contract workers less in the face of demand shocks. This points to our results being driven by machinery producing industries compared to non-machinery industries.

An important question may arise following our results: are firms adopting labour-saving technologies in their production process when investing in computer capital? One way that we check this is by looking at the impact of rainshock on contract work in the core production processes and the non-core production processes. The ASI data records information on man-days (the number of workers in a day summed over all days in a year) separately for manufacturing and non-manufacturing works. Manufacturing work includes activities that are directly relevant to the main production process (considered as "core" activities), whereas non-manufacturing work (considered as "non-core" activities) includes peripheral

[15]Machinery production industries include, for example, industries producing office accounting machinery, communication devices, electrical machinery and transport equipment, whereas non machinery production industries include industries producing food and beverages, tobacco products, textiles, rubber products and chemical products. Non-machinery industries include industries up to classification number 28 in Appendix A.1, whereas classification number 29 onward are considered machinery industries.

works such as security, cleaning services, etc.[16] Contract workers on average are mostly involved in the core manufacturing process (Table 1). We check if the interaction of our computer capital dummy and rainshock has different or similar impacts across the two types of contract work.

In Table 6 we find that the coefficient on the interaction term is statistically significant and negative for manufacturing contract work (column 1). Firms on average increase the number of contract manufacturing man-days by 408.47 when faced with a demand shock. However, firms with above-average computer capital share carry out contract work by 715.02 fewer man-days than other firms facing a demand shock. Impact on manufacturing man-days would imply that contract employment is mainly affected for the core production processes, essentially the contract workers on the factory floor. This could possibly point to an automation impact of computer capital investment, as contract hiring for the main production process goes down. On the other hand, we do not find any statistically significant impact of the interaction term on non-manufacturing man-days. Thus, it is not the case that contract hiring for peripheral activities are being affected due to computer capital investment in response to demand shocks. This confirms that contract hiring by firms following demand shocks is relatively lower in the main production process, possibly pointing to a labour-saving effect of computer capital in the main production process.

Why do firms differ in hiring decisions in response to transitory demand shocks depending on their level of computer capital expenditure? It is quite possible that more technologically advanced firms do not require as many contract workers in their manufacturing process.[17] A firm investing in above-average computer capital share may require relatively fewer contract workers for production compared to firms with lower-than-average computer capital share.

[16]The terminology "core" and "non-core" was used by Chaurey and Soundararajan (2019).

[17]We are referring to the labour-substitution effect of technology which removes workers from the manufacturing process (Acemoglu and Autor (2011), Aghion et al. (2020)).

Following positive demand shocks, firms hire more contract workers to cater to an increase in demand for industrial products. However, firms investing in computer capital may require relatively fewer contract workers to produce industrial products. Therefore, these firms will also demand relatively fewer contract workers to produce additional output facing demand shocks. Thus, even when there is a demand surge, these firms do not need to hire as many workers to cater to the increase in demand.

We also carry out robustness checks and present them in Table 7. Firms of certain industries may choose to locate in certain states, leading to different industry distributions between states. We add state-industry fixed effects to control for non-random location decisions of firms and find that our results are similar (column 1). Firms may be subject to changes in state specific labour laws. We account for this by adding state-year fixed effects and our results remain unchanged (column 2). As a robustness check, we also control for the share of agricultural inputs a firm purchases in a given year. Rainfall shocks affect agriculture yield and agricultural productivity. As a result, supply and price of agricultural products are affected during rainfall shocks. Some firms are relatively more dependent on inputs from the agriculture sector. For example, relatively more inputs are required from the agricultural sector for firms in the food and beverages industry and textile industry. These firms will face a change in the supply and price of most of their inputs during rainfall shocks, compared to firms not dependent on the agriculture sector for inputs. Firms that use agricultural inputs may account for these changes and optimize their costs during rainfall shocks and then hire workers as required. We control for such price and quantity changes on the input side for a firm. In column 3 we control for the share of agricultural inputs in a firm's total quantity of inputs in a given year, while in column 4 the share of expenditure on agricultural inputs in the total expenditure on inputs is controlled for.[18]

[18]The ASI records quantity and purchase value of inputs. Inputs are classified according to the Annual Survey of Industries Commodity Classification (ASICC). We consider ASICC 2-digit codes from 11 to 16

Our results are not sensitive to adding agricultural input controls.

4.2 Alternative Measures

Next we construct a host of alternative measures of a firm's computer capital expenditure share, and run the main regression with these alternative measures. These regression results are reported in Table 8. In column 1, $Compshare_{idt}$ is the computer capital share in total capital of firm i in district d in year t. It is a continuous variable as opposed to the dummy variable $Compdum_{idt}$ that we have used so far. The interaction term (computer capital share and rainfall shock) is again statistically significant and negative. This implies that compared to firms that invest relatively less in computer capital, firms that invest more in computer capital are less likely to hire as many contract workers in response to positive rainfall shocks. An increase of one standard deviation in the share of computer capital expenditure of a firm leads to a decline in contract hiring by 1.24 (0.28*4.41) following positive demand shocks. Our result also implies that a 10 percentage point increase in computer capital share leads to a reduction in average contract hiring by 2.8 workers in the face of demand shocks. In column 2, we consider a dummy $Compmed_{idt}$ that takes value 1 if the computer capital share of a firm in a year is above the median computer capital share (1.31%) of the sample, and 0 otherwise. That is, we use the sample median instead of the sample mean to define our computer capital dummy. Again, the coefficient is negative and statistically significant. A firm with computer capital share above the median hires 1.7 fewer contract workers compared to firms with lower-than-median computer capital share in the face of demand shocks.

We also construct another dummy ($Compind_{idt}$) that takes value 1 if computer capital share of a firm in a year is above the industrial average computer capital share in the

as agricultural inputs.

sample, and 0 otherwise. This measure considers that the average computer capital share may vary across industries. Some industries invests more in computer capital depending on the nature of goods produced by these industries compared to others.[19] In column 3 of Table 8 we find that the interaction term is statistically significant and negative. A firm that has computer capital share above its industry average hires 2 fewer contract workers in the face of a positive rainfall shock. We also consider the average computer capital share within each state and industry. We construct a dummy $Compindstt_{idt}$ that takes value 1 if a firm's computer capital share in a year is above the average computer capital share of its state and industry, and 0 otherwise. This alternative measure considers that average computer capital expenditure could vary across states also (which may be due to various reasons such as state laws and resources). Once again our results are similar to the previous measures. Column 4 of Table 8 shows that the coefficient on the interaction term with this measure is statistically significant and negative. Contract hiring is lower by 1.55 when a firm has above average computer capital expenditure in its state and industry.

We now use the US data on average computer capital for the period 2002-2010 to construct another set of alternative measures of computer capital share. The US based measures may be far more stringent since the US computer capital investment in an industry is relatively more than India as the US is far more advanced technologically.[20] The results are reported in Table 9. Column 1 considers the dummy $CompdumUS_{idt}$ that takes value 1 if the computer capital share of a firm in a year is above the average US computer

[19] For example, firms in food and beverage industry have lower computer capital share than firms in the publishing and printing industry. For a list of average computer capital shares by industry, please refer to Appendix A.2.

[20] For example, the average US computer capital share for the period 2002-2010 is 6.02%, whereas the average computer capital share for the same period is only 2.84% for Indian firms. In Appendix A.3, we compare five industries with the highest computer capital shares in year 2002 between US and India. We make a similar comparison for 2010. We find that the magnitude of computer capital shares for the Indian industries is much lower than that of the US for both years. We also find that while the industries are relatively different for India and US in 2002, but they have become relatively similar in 2010. This may suggest that India's computer-aided technology pace is slow and is becoming similar to the US over time.

capital share for the period 2002-2010, and 0 otherwise. In column 2 we consider a dummy $CompyrUS_{idt}$ that takes value 1 if the computer capital share of a firm in a year is above the US average computer capital share for that year, and 0 otherwise. In column 3 we run our regression with the dummy $CompindUS_{idt}$, which takes value 1 if the computer capital share of a firm in a year is above the corresponding US industrial average for the period 2002-10, and 0 otherwise. Finally, column 4 considers variation at the industry and year level: $CompindyrUS_{idt}$ takes value 1 if the computer capital share of a firm in a year is above the corresponding US industrial average for that year, and 0 otherwise. In all cases, irrespective of heterogeneity based on the period, year or industry, we find that the coefficient of the interaction term is statistically significant and negative. Firms that are technologically advanced (in terms of computer capital investment) similar to levels of the US, do not hire as many contract workers when exposed to transitory demand shocks. Thus, our results are robust when we consider exogenous US based measures for creating a dummy capturing computer capital heterogeneity across firms. Our corresponding results based on Indian computer capital measures also hold for the period 2002-2010 and are reported in Appendix A.4.

The above described measures are time variant since the dummy is allowed to change in any year if the firm invests more (or less) than the sample average in that year. We also consider a set of measures that classify firms based on the firm's computer capital expenditure at the starting year. These measures do not account for any temporal changes in computer capital expenditure of a firm. We construct an alternative measure $compalt_{id}$ that takes value 1 if the computer capital share of the firm in the first sampling year is above the average computer capital share in the first sampling year, and 0 otherwise. Column 1 of Table 10 reports the coefficient on the interaction term for this dummy and the results are similar as before: statistically significant and negative. We also classify firms based on the industrial average computer capital expenditure in the first sampling year of the firm: $compaltind_{id}$ takes value 1 if the firm's computer capital share in the first sampling year is above its industry average computer capital share in the first sampling year, and 0 otherwise. As column 2 of Table 10 demonstrates, our results are robust to this measure too.

From the above analysis we can conclude that our results are not dependent on the type of computer capital measure we use. Our results are similar and consistent across a host of alternative computer capital measures. Given our estimates, we can conclude that computer capital investment allows a firm to reduce contract worker hiring during transitory demand shocks. It is possible that firms investing in computer capital are less dependent on contract workers when producing output. Therefore, when a demand shock arises, firms investing in computer capital do not need to employ as many additional contract workers to produce the additional output. Hence, these firms hire fewer contract workers to cater to short term changes in output in response to demand shocks, compared to firms that invest relatively less in computer capital. Firms investing in computer capital seem to be relatively protected against demand shocks, positive as well as negative, and can therefore avoid flexible hiring or firing of contract workers (in the sense that they do not need to rely on availability of contract workers in response to demand fluctuations).

5 Conclusion

The literature has focused on the impact of different types of technology on employment – from computers (Autor et al. (1998), Autor et al. (2003)) to robotics and artificial intelligence (Acemoglu and Restrepo (2020), Acemoglu et al. (2020)). There is no doubt that establishments are adopting technologies to secure a leaner manufacturing process, as automation has already displaced workers from their occupations on a global scale (ILO (2019)). However, in developing countries or emerging economies, technology adoption might not be homogeneous across all firms given political, organizational or other factors. Even in developed countries, adopting certain technologies is more prevalent in specific sectors (for example, robotics in automobile sector (Acemoglu and Restrepo (2020))). Thus, differences in firm decisions may arise due to heterogeneous technology adoption.

We study how a firm's hiring decisions in response to demand shocks are affected by investment in computer capital in India for the period 2000-2010. Transitory demand shocks, business cycles or other economic disturbances affect a firm's decisions on employment, output and prices. Given that firms are innovating, examining how hiring decisions in response to demand shocks have changed due to heterogeneous technology adoption is important. We focus on computer capital in our study, as the use of computers and computer-aided technology has risen significantly post World War II (Acemoglu and Autor (2011)). In India, analyzing computer technology (instead of say, robotics) is more relevant given India's technological pace (Berman et al. (2005)) and growth in demand for computer-aided technologies (Erumban and Das (2020), IBEF (2008)).

As we are looking at transitory demand shocks, we focus on contract workers. Contract workers are not covered by India's primary labour regulation, the Industrial Disputes Act (1947), unlike permanent or regular workers. Hence, firms tend to hire or fire contract workers during transitory demand shocks to cater to any short-term demand changes (Chaurey (2015)). Following the previous literature (Adhvaryu et al. (2013), Chaurey (2015)), we construct lagged rainfall shocks to proxy for demand shocks. We find that firms with above average computer share tend to hire or fire less in response to demand shocks. The reduction is by 2.32 workers which is 11.33% of the sample mean. Our main results are not sensitive to controlling for non-random location of industries, state specific labour laws, expenditure on agricultural inputs and the source of rainfall data.

As robustness checks, we construct a host of alternate computer capital investment measures. We find that contract employment following rainfall shocks is negatively associated with computer capital expenditure share in total expenditure. A 10 percentage point increase in computer capital expenditure share is associated with a decline in hiring and firing in response to demand shocks for firms by 2.8 contract workers. We also construct alternate measures such as a dummy for above-median computer capital share, industrial average computer capital share, industry-state average computer capital share and a number of US based alternative measures. We also classify firms based on their computer capital in the first sampling year. Our results are not sensitive to the type of measure we use.

Our study shows that heterogeneity in firm decisions of contract employment arises due to differences in computer capital expenditure. Reduction in hiring in response to positive demand shocks seem to imply that firms are investing in labour-saving technologies. As firms do not need to hire as many contract workers facing positive demand shocks, it may imply that computer capital investing firms do not require contract workers in parts of their manufacturing process. Our results point to firms possibly automating segments of their manufacturing process when investing in computer capital. Even though our results are for the period 2000-2010, they seem to be in line with recent reports about automation displacing low-skilled workers (ILO-IOE (2019)). Thus, Indian firms with computer capital investments seem to be adopting leaner manufacturing processes in terms of reducing their dependence on contract employment in response to transitory demand shocks.

References

Aboal, D., Garda, P., Lanzilotta, B., and Perera, M. (2015). Innovation, firm size, technology intensity, and employment generation: Evidence from the Uruguayan manufacturing sector. *Emerging Markets Finance and Trade*, 51(1):3–26.

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2020). AI and jobs: Evidence from online vacancies. Working Paper 28257, National Bureau of Economic Research.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Adhvaryu, A., Chari, A. V., and Sharma, S. (2013). Firing costs and flexibility: Evidence from firms' employment responses to shocks in India. *The Review of Economics and Statistics*, 95(3):725–740.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2020). What are the labor and product market effects of automation? New evidence from France. *CEPR Discussion Paper No. DP14443*.

Autor, D. and Salomons, A. (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share. Working Paper 24871, National Bureau of Economic Research.

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics*, 113(4):1169–1213.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Basu, A. K., Chau, N. H., and Soundararajan, V. (2021). Contract employment as a worker discipline device. *Journal of Development Economics*, 149:102601.

Berman, E., Somanathan, R., and Tan, H. W. (2005). Is skill-biased technological change here yet? Evidence from Indian manufacturing in the 1990's. *Annals of Economics and Statistics*, No.79/80:299–321.

Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Economic Policy*, 34(100):589–626.

Bessen, J. E., Goos, M., Salomons, A., and Van den Berge, W. (2019). Automatic reaction - What happens to workers at firms that automate? *Boston University School of Law, Law and Economics Research Paper*, (19-2).

Bhandari, A. K. and Heshmati, A. (2008). Wage inequality and job insecurity among permanent and contract workers in India: Evidence from organized manufacturing industries. *ICFAI Journal of Applied Economics*, 7(1):80–111.

Blanchflower, D. G. and Burgess, S. M. (1998). New technology and jobs: Comparative evidence from a two country study. *Economics of Innovation and New Technology*, 5(2-4):109–138.

Chaurey, R. (2015). Labor regulations and contract labor use: Evidence from Indian firms. *Journal of Development Economics*, 114:224–232.

Chaurey, R. and Soundararajan, V. (2019). Banning contract work: Implications for input choices and firm performance. *Indian Institute of Management Bangalore Repository 2010-2019P*. https://repository.iimb.ac.in/handle/2074/13956.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.

Doms, M., Dunne, T., and Roberts, M. J. (1995). The role of technology use in the survival and growth of manufacturing plants. *International Journal of Industrial Organization*, 13(4):523–542.

Erumban, A. A. and Das, D. K. (2020). ICT investment and economic growth in India: An industry perspective. In *Digitalisation and Development*, pages 89–117. Springer, Singapore.

Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in Africa. *American Economic Review*, 109(3):1032–79.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences*, 107(35):15367–15372.

IBEF (2008). Machine tools market and opportunities, a report by Klynveld Peat Marwick Goerdeler (KPMG) for Indian Brand Equity Foundation (IBEF). https://www.ibef.org/download/Machine_Tools_170708.pdf.

ILO-IOE (2019). Changing business and opportunities for employer and business organizations. *International Labour Office and International Organisation of Employers – Geneva*. https://www.ilo.org/actemp/areas-of-work/WCMS_679582/lang--en/index.htm.

Jayachandran, S. (2006). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy*, 114(3):538–575.

Jones, B. F. and Olken, B. A. (2010). Climate shocks and exports. *American Economic Review*, 100(2):454–59.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35–78.

Kaur, S. (2019). Nominal wage rigidity in village labor markets. *American Economic Review*, 109(10):3585–3616.

Nizalova, O. Y. and Murtazashvili, I. (2016). Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5(1):71–77.

Shepard, D. (1968). A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM National Conference*, pages 517–524.

Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827.

Tinbergen, J. (1974). Substitution of graduate by other labour. *Kyklos: International Review for Social Sciences*, 27(2):217–226.

Tinbergen, J. (1975). *Income Differences: Recent Research*. North-Holland Publishing Company, Amsterdam.

Van Reenen, J. (1997). Employment and technological innovation: Evidence from UK manufacturing firms. *Journal of Labor Economics*, 15(2):255–284.

Vashisht, P. (2018). Destruction or polarization: Estimating the impact of technology on jobs in Indian manufacturing. *The Indian Journal of Labour Economics*, 61(2):227–250.

Willmott, C. J. and Matsuura, K. (2018). Terrestrial precipitation: 1900-2017 gridded monthly time series. http://climate.geog.udel.edu/~climate/html_pages/Global2017/README.GlobalTsP2017.html.

Willmott, C. J., Rowe, C. M., and Philpot, W. D. (1985). Small-scale climate maps: A sensitivity analysis of some common assumptions associated with grid-point interpolation and contouring. *The American Cartographer*, 12(1):5–16.

Yeaple, S. R. (2005). A simple model of firm heterogeneity, international trade, and wages. *Journal of International Economics*, 65(1):1–20.

Zhang, P., Deschenes, O., Meng, K., and Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1–17.

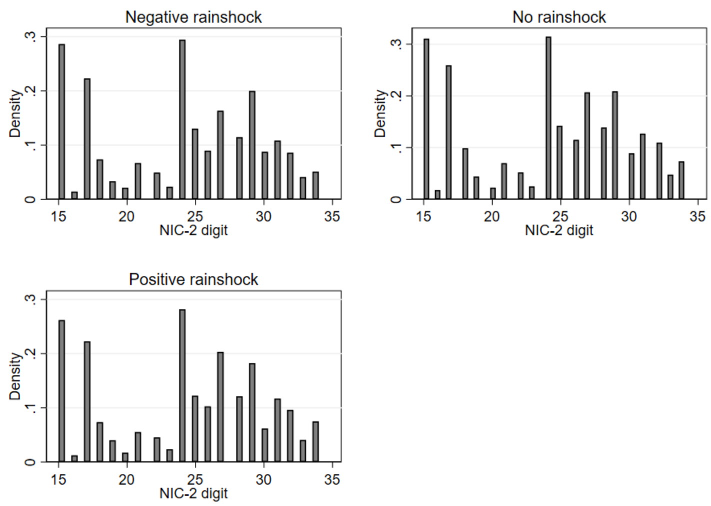

Figure 1: 2-digit industries distribution across different rain shock years

Note: Data sources are the Annual Survey of Industries (ASI), rounds 1999-2000 to 2009-2010. The 2-digit industry classification is provided in Appendix A.1.

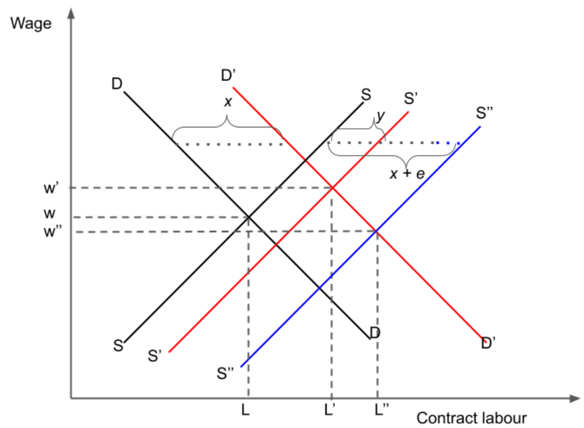

Figure 2: Positive labour demand and positive labour supply

Note: Supply shift y is less than the demand shift x. Supply shift $x + e$ is more than the demand shift x.

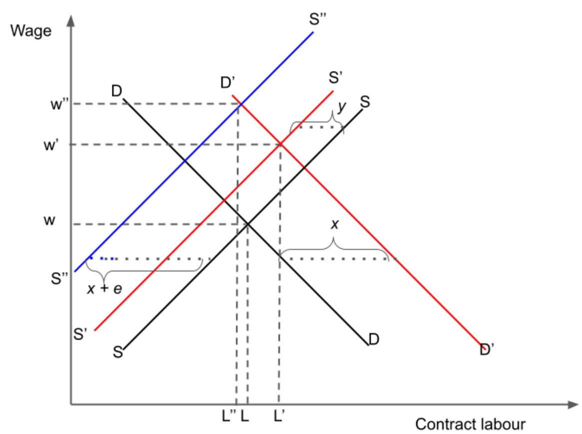

Figure 3: Positive labour demand and negative labour supply

Note: Supply shift y is less than the demand shift x. Supply shift $x + e$ is more than the demand shift x.

Table 1: Summary statistics

	(1) All firms	(2) Firms with above avg computer share	(3) Firms with below avg computer share
Total capital (mil Rs.)	85.59	49.45	99.53
	(232.52)	(160.16)	(253.64)
Computer capital (mil Rs.)	1.37	2.78	0.83
	(4.18)	(6.25)	(2.84)
Computer capital share	2.88	7.77	1.00
in total capital (%)	(4.41)	(5.94)	(0.76)
Regular workers (number)	47.55	43.14	49.25
	(86.66)	(84.30)	(87.50)
Contract workers (number)	20.47	16.34	22.06
	(59.39)	(52.55)	(61.75)
Contract workers share	18.96	16.88	19.76
in total workers (%)	(32.41)	(31.31)	(32.80)
Contract manufacturing	6317.21	4979.61	6833.39
man-days	(18625.07)	(16239.97)	(19443.03)
Contract non-manufacturing	0.67	0.23	0.84
man-days	(9.23)	(5.56)	(10.30)
Rural firms (fraction)	0.40	0.23	0.40
	(0.49)	(0.42)	(0.49)
Negative rainshock (fraction)	0.16	0.16	0.16
	(0.36)	(0.36)	(0.36)
Positive rainshock (fraction)	0.20	0.19	0.20
	(0.40)	(0.40)	(0.40)
Observations	81635	21780	59855

Note: Data is from the Annual survey of Industries (ASI) from round 1999-2000 to 2009-2010. Observations are weighted by ASI sample weights. Standard deviation in parentheses. All employment and capital values above the 99th percentile are equated to the 99th percentile value to remove influence of outliers. Column 1 includes all firms. Column 2 includes firms with computer capital share greater than average computer capital share of all firms. Column 3 includes firms with computer capital share less than or equal to average computer capital share of all firms. Total workers include contract workers and regular workers.

Table 2: Firm-level computer measures

	(1)	(2)
Outcome: Contract workers		
$Rainshock_{dt-1}$	1.26**	1.31***
	(0.49)	(0.50)
$Compdum_{idt}$	-0.32	-0.47
	(1.19)	(1.17)
$Compdum_{idt} * Rainshock_{dt-1}$	-1.98***	-2.32***
	(0.74)	(0.82)
Observations	64340	64340
R^2	0.770	0.772
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	No	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Firm-level data is from the Annual Survey of Industries (2000-2010). $Compdum_{idt}$ takes value 1 if the computer capital share of a firm in year t is above the sample average computer capital share of the sample (2000-2010). Rainfall data is from Center for Climatic Research University of Delaware. $Rainshock_{dt-1}$ takes value 1 if annual rainfall in district d in year $t-1$ is above the 80^{th} percentile, -1 if rainfall in a district in year $t-1$ is below the 20^{th} percentile of the rainfall distribution, and 0 otherwise. Age controls includes the age and age squared of a firm.

Table 3: Rural and urban sectors

Outcome: Contract workers	(1) Rural	(2) Urban
$Rainshock_{dt-1}$	1.91**	0.90
	(0.81)	(0.55)
$Compdum_{idt}$	-1.58	0.01
	(2.45)	(1.42)
$Compdum_{idt} * Rainshock_{dt-1}$	-4.74***	-1.34
	(1.70)	(0.83)
Observations	26685	33474
R^2	0.791	0.772
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	Yes	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Column 1 restricts the sample to rural sector firms. Column 2 restricts the sample to urban sector firms.

Table 4: Asymmetric rainfall shocks

Outcome: Contract workers	(1) Positive shock	(2) Negative shock
$PositiveRainshock_{dt-1}$	1.12	
	(0.75)	
$Compdum_{idt} * PositiveRainshock_{dt-1}$	-2.62**	
	(1.09)	
$NegativeRainshock_{dt-1}$		-1.93***
		(0.63)
$Compdum_{idt} * NegativeRainshock_{dt-1}$		2.86**
		(1.19)
$Compdum_{idt}$	0.00	-0.97
	(1.20)	(1.14)
Observations	64340	64340
R^2	0.772	0.772
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	Yes	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. $PositiveRainshock_{dt-1}$ takes value 1 if rainfall in district d in year $t-1$ is above the 80^{th} percentile of the distribution, and 0 otherwise. $NegativeRainshock_{dt-1}$ takes value 1 if rainfall in district d in year $t-1$ is below the 20^{th} percentile of the distribution, and 0 otherwise.

Table 5: Machinery industries

	(1)	(2)
Outcome: Contract workers	Non-machinery	Machinery
$Rainshock_{dt-1}$	0.94**	2.63**
	(0.47)	(1.28)
$Compdum_{idt}$	-0.50	-0.20
	(1.50)	(1.87)
$Compdum_{idt} * Rainshock_{dt-1}$	-1.72	-4.02**
	(1.07)	(1.63)
Observations	46591	16911
R^2	0.778	0.764
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	Yes	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Non-machinery industries include food, beverage, textile, wood, coke, basic metals (up to 2-digit classification 28 in Appendix A.1). Machinery industries include office, accounting, computing, communication, medical, electrical machinery, transport, manufacturing not elsewhere classified (from 2-digit classification 29 in Appendix A.1).

Table 6: Manufacturing versus non-manufacturing contract work

Outcome: Contract Man-days	(1) Manufacturing Man-days	(2) Non-manufacturing Man-days
$Rainshock_{dt-1}$	408.47**	0.08
	(165.62)	(0.18)
$Compdum_{idt}$	-157.45	-0.18
	(362.27)	(0.14)
$Compdum_{idt} * Rainshock_{dt-1}$	-715.02***	-0.16
	(258.36)	(0.17)
Observations	64340	64340
R^2	0.769	0.520
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	Yes	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Man-days represent the total number of days worked and paid for during the year. It is computed by summing-up the number of workers per day over all days. Manufacturing refers to activities involved in the main production process. Non-manufacturing refers to activities that are peripheral to the production process.

Table 7: Robustness checks

Outcome: Contract workers	(1) State-industry	(2) State-year	(3) Agri quantity	(4) Agri price
$Rainshock_{dt-1}$	1.26**	1.55**	1.34***	1.33***
	(0.49)	(0.63)	(0.50)	(0.50)
$Compdum_{idt}$	-0.60	-0.51	-0.50	-0.50
	(1.18)	(1.18)	(1.18)	(1.17)
$Compdum_{idt} * Rainshock_{dt-1}$	-2.27***	-2.42***	-2.30***	-2.30***
	(0.82)	(0.81)	(0.81)	(0.82)
Observations	64330	64339	64154	64288
R^2	0.774	0.774	0.772	0.772
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry year FE	Yes	Yes	Yes	Yes
State industry FE	Yes	No	No	No
State year FE	No	Yes	No	No
Age controls	Yes	Yes	Yes	Yes
Agriculture quantity controls	No	No	Yes	No
Agriculture price controls	No	No	No	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Agriculture quantity controls refers to share of agriculture inputs in total quantity of indigenous inputs of a firm in a year. Agriculture price controls refers to share of firm expenditure on agricultural inputs in total indigenous inputs of a firm in a year. ASI records quantity and purchase value of inputs. Inputs are classified according to the Annual Survey of Industries Commodity Classification (ASICC). ASICC 2-digit codes 11-16 are considered as agricultural inputs.

Table 8: Alternative measures 1

Outcome: Contract workers	(1) Share	(2) >Median	(3) >Industry average	(4) >Industry-state average
$Rainshock_{dt-1}$	1.48***	1.54**	1.28**	1.16**
	(0.52)	(0.63)	(0.52)	(0.52)
$Compshare_{idt}$	-0.17			
	(0.15)			
$Compshare_{idt} * Rainshock_{dt-1}$	-0.28***			
	(0.08)			
$Compmed_{idt}$		0.46		
		(1.06)		
$Compmed_{idt} * Rainshock_{dt-1}$		-1.70**		
		(0.73)		
$Compind_{idt}$			-0.79	
			(1.03)	
$Compind_{idt} * Rainshock_{dt-1}$			-2.00**	
			(0.82)	
$Compindstt_{idt}$				-0.84
				(0.89)
$Compindstt_{idt} * Rainshock_{dt-1}$				-1.55*
				(0.82)
Observations	64340	64340	64340	64340
R^2	0.772	0.772	0.772	0.772
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. In column 1, $Compshare_{idt}$ refers to computer capital share for a firm in a year. Median computer capital share, industry average and industry-state average computer capital share are calculated for the sample from 2000 to 2010. In column 2, $Compmed_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the median computer capital share, and 0 otherwise. In column 3, $Compind_{idt}$ takes value 1 if computer capital share of a firm in a year is above the average computer capital share in the industry of the firm, and 0 otherwise. In column 4, $Compindstt_{idt}$ takes value 1 if computer capital share of a firm in a year is above the average computer capital share in the industry and state of the firm, and 0 otherwise. Results are reported for the period 2000-2010.

Table 9: Alternative measures 2

Outcome: Contract workers	(1) >Period average	(2) >Year average	(3) >Industry average	(4) >Industry-year average
$Rainshock_{dt-1}$	1.06**	1.05**	1.10**	0.99*
	(0.50)	(0.50)	(0.49)	(0.51)
$CompdumUS_{idt}$	0.62			
	(1.42)			
$CompdumUS_{idt} * Rainshock_{dt-1}$	-2.60**			
	(1.10)			
$CompyrUS_{idt}$		1.16		
		(1.17)		
$CompyrUS_{idt} * Rainshock_{dt-1}$		-2.38**		
		(1.13)		
$CompindUS_{idt}$			-1.99**	
			(0.99)	
$CompindUS_{idt} * Rainshock_{dt-1}$			-2.76***	
			(0.91)	
$CompindyrUS$				-3.30***
				(0.96)
$CompindyrUS_{idt} * Rainshock_{dt-1}$				-1.70*
				(1.03)
Observations	59945	59945	59945	59945
R^2	0.780	0.780	0.780	0.780
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. Data on average US computer capital share is from the Annual Survey of Manufactures. In column 1, $CompdumUS_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the average US computer capital share for the period 2002-2010, and 0 otherwise. In column 2, $CompyrUS_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the average US computer capital share for that year, and 0 otherwise. In column 3, $CompindUS_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the corresponding US industry average for the period 2002-2010, and 0 otherwise. In column 4, $CompindyrUS_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the corresponding US industry average for that year, and 0 otherwise. Results are for the period 2002-2010.

Table 10: Alternative measures 3

Outcome: Contract workers	(1) Sample average	(2) Industry average
$Rainshock_{dt-1}$	1.10**	1.14**
	(0.50)	(0.50)
$Compalt_{id} * Rainshock_{dt-1}$	-1.67*	
	(0.89)	
$Compaltind_{id} * Rainshock_{dt-1}$		-1.73**
		(0.83)
Observations	55983	55983
R^2	0.870	0.870
Firm FE	Yes	Yes
Year FE	Yes	Yes
Industry year FE	Yes	Yes
Age controls	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Observations are weighted by sample weights. In column 1, $Compalt_{id}$ takes value 1 for a firm throughout the period if the computer capital share in the starting year of the firm in the sample is above the average computer capital share in that year. In column 2, $Compaltind_{id}$ takes value 1 for a firm throughout the period if the computer capital share in the starting year of the firm in the sample is above its industry average computer capital share. Results are reported for the period 2000-2010.

A Appendix

A.1 Industry categories

Firms are classified into industries according to the National Industrial Classification (NIC). In the ASI, firms are classified by the National Industrial Classification (NIC) which is available at the 5-digit level for most years in our sample. The higher the number of digits used to describe the industry the more detailed is the industry description. NIC has undergone some changes in its classification system over the years. Data for years before 2004 follow the NIC-98 classification whereas the data for 2004 to 2007 follows NIC-04. Year 2008 onward, firms are classified by NIC-08. To maintain consistency of industrial classification, we match industries at the 2-digit level, following the detailed industry descriptions provided by MoSPI (Ministry of Statistics and Programme Implementation). Table A1 lists the industry categories.

A.2 Average computer capital shares by industry

Table A2 reports the average computer share of a firm within its industry. Manufacture of office, accounting equipment, radio, television, communication equipment and medical and optical instruments record the highest average computer capital share (7.26). Manufacture of basic metals records the lowest average computer capital share (1.27).

A.3 US and India average computer capital share

Table A3 reports the top five industries with the highest computer capital shares in the year 2002 for India (Panel A) and US (Panel B). Computer capital shares for the top five industries for India is lower than that of the US. Table A4 reports the top five industries with the highest computer capital shares in the year 2010 for India (Panel A) and US (Panel B). Again, the computer capital shares are much lower for Indian industries than for the US industries. It is interesting to note that the top five industries are similar across the two countries in the year 2010 as compared to the year 2002. This may suggest that investments in computer capital and possibly use of computer-aided technology used by Indian industries have become similar to the US over time, even though the share is much less than the US. The correlation between US and Indian yearly industrial average computer capital share for the period 2002-2010 is 0.63. If we consider a breakup of the sample period into three-year periods the correlation is 0.54 (2002-2004), 0.67 (2005-2007) and 0.69 (2008-2010) suggesting that India is "catching up" to US computer capital investment.

A.4 Indian computer capital measures, 2002-2010

In Table A5, we report our results for the period 2002-2010 to check that our results do not change when we change the period of analysis from 2000-2010. Our results hold for all the measures. The measures are constructed in a manner similar to those constructed for the US measures in section 4.2.

Table A1: 2-digit Industry

S. No.	Industry
15	Manufacture of food products and beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel; dressing and dyeing of fur
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery,harness and footwear
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21	Manufacture of paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Manufacture of chemicals and chemical products
25	Manufacture of rubber and plastics products
26	Manufacture of other non-metallic mineral products
27	Manufacture of basic metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office, accounting and computing machinery manufacture of radio, television and communication equipment and apparatus manufacture of medical, precision and optical instruments, watches and clocks
31	Manufacture of electrical machinery and apparatus n.e.c.
32	Manufacture of motor vehicles, trailers and semi-trailers
33	Manufacture of other transport equipment
34	Manufacture of furniture; manufacturing n.e.c.

Note: Industry at 2-digit level, concordance has been carried out between NIC-04 and NIC-08 2-digit categories.

Table A2: Average computer capital share

Industry	Average computer share
Manufacture of food products and beverages	1.62
Manufacture of tobacco products	3.79
Manufacture of textiles	1.42
Manufacture of wearing apparel; dressing and dyeing of fur	3.90
Tanning and dressing of leather; manufacture of luggage, handbags, saddlery,harness and footwear	2.89
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	1.87
Manufacture of paper and paper products	2.10
Publishing, printing and reproduction of recorded media	5.84
Manufacture of coke, refined petroleum products and nuclear fuel	1.96
Manufacture of chemicals and chemical products	2.48
Manufacture of rubber and plastics products	1.98
Manufacture of other non-metallic mineral products	1.64
Manufacture of basic metals	1.27
Manufacture of fabricated metal products, except machinery and equipment	3.22
Manufacture of machinery and equipment n.e.c.	5.40
Manufacture of office, accounting and computing machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks	7.26
Manufacture of electrical machinery and apparatus n.e.c.	5.16
Manufacture of motor vehicles, trailers and semi-trailers	2.91
Manufacture of other transport equipment	2.83
Manufacture of furniture; manufacturing n.e.c.	4.51

Note: Industry at 2-digit level, concordance has been carried out between NIC-04 and NIC-08 2-digit categories. Average computer capital share is the average computer capital share of firms within each industry (sample weights applied).

Table A3: Top 5 industries by computer capital share, India and US 2002

Industry	Computer capital share
Panel A: India	
Manufacture of office, accounting and computing machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks	7.63
Publishing, printing and reproduction of recorded media	7.54
Manufacture of tobacco products	6.42
Manufacture of machinery and equipment n.e.c.	5.24
Manufacture of electrical machinery and apparatus n.e.c.	4.70
Panel B: US	
Manufacture of wearing apparel; dressing and dyeing of fur	13.93
Manufacture of furniture; manufacturing n.e.c.	12.59
Tanning and dressing of leather; manufacture of luggage, handbags, saddlery,harness and footwear	11.50
Publishing, printing and reproduction of recorded media	10.79
Manufacture of office, accounting and computing machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks	9.72

Note: US computer capital shares by industry computed from Annual Survey of Manufactures data (2002). Indian computer capital shares constructed from Annual Survey of Industries data (2002).

Table A4: Top 5 industries by computer capital share, India and US 2010

Industry	Computer capital share
Panel A: India	
Manufacture of office, accounting and computing machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks	7.69
Publishing, printing and reproduction of recorded media	5.46
Manufacture of machinery and equipment n.e.c.	5.34
Manufacture of furniture; manufacturing n.e.c.	5.02
Manufacture of electrical machinery and apparatus n.e.c.	4.68
Panel B: US	
Manufacture of wearing apparel; dressing and dyeing of fur	12.90
Manufacture of office, accounting and computing machinery, manufacture of radio, television and communication equipment and apparatus, manufacture of medical, precision and optical instruments, watches and clocks	12.17
Manufacture of furniture; manufacturing n.e.c.	11.15
Publishing, printing and reproduction of recorded media	10.80
Manufacture of machinery and equipment n.e.c.	7.29

Note: US computer capital shares by industry computed from Annual Survey of Manufactures data (2010). Indian computer capital shares constructed from Annual Survey of Industries data (2010).

Table A5: India-based measures

	(1)	(2)	(3)	(4)
Outcome: Contract workers				
$Rainshock_{dt-1}$	1.47***	1.46***	1.30**	1.26**
	(0.56)	(0.56)	(0.59)	(0.61)
$Compdum_{idt}$	-0.57			
	(1.14)			
$Compdum_{idt} * Rainshock_{dt-1}$	-2.73***			
	(0.92)			
$Compyr_{idt}$		-1.53		
		(1.12)		
$Compyr_{idt} * Rainshock_{dt-1}$		-2.70***		
		(0.94)		
$Compind_{idt}$			-1.25	
			(1.19)	
$Compind_{idt} * Rainshock_{dt-1}$			-1.88**	
			(0.90)	
$Compindyr_{idt}$				-1.00
				(1.08)
$Compindyr_{idt} * Rainshock_{dt-1}$				-1.72*
				(0.98)
Observations	59945	59945	59945	59945
R^2	0.780	0.780	0.780	0.780
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry year FE	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes

Note: *p<0.1, **p<0.05, ***p<0.01. Standard errors clustered at the district level. Results are for the period 2002-2010. Data on computer capital share is from the Annual Survey of Industries. Observations are weighted by sample weights. In column 1, $Compdum_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the period average computer capital share, and 0 otherwise. In column 2, $Compyr_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the average computer capital share for that year, and 0 otherwise. In column 3, $Compind_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the industry average computer capital share for the period, and 0 otherwise. In column 4, $Compindyr_{idt}$ is a dummy that takes value 1 if the firm's computer capital share in a year is above the industry average computer capital share for that year, and 0 otherwise.