Organizational Barriers to Technology Adoption: Evidence from Soccer-Ball Producers in Pakistan*

David Atkin[†], Azam Chaudhry[‡], Shamyla Chaudry[§], Amit K. Khandelwal[¶] and Eric Verhoogen[‖]

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Abstract

This paper studies technology adoption in a cluster of soccer-ball producers in Sialkot, Pakistan. Our research team invented a new cutting technology that reduces waste of the primary raw material. We allocated the technology to a random subset of producers. Despite the arguably unambiguous net benefits of the technology for nearly all firms, after 15 months take-up remained puzzlingly low. We hypothesize that an important reason for the lack of adoption is a misalignment of incentives within firms: the key employees (cutters and printers) are typically paid piece rates, with no incentive to reduce waste, and the new technology slows them down, at least initially. Fearing reductions in their effective wage, employees resist adoption in various ways, including by misinforming owners about the value of the technology. To investigate this hypothesis, we implemented a second experiment among the firms to which we originally gave the technology: we offered one cutter and one printer per firm a lump-sum payment, approximately equal to a monthly wage, that was conditional on them demonstrating competence in using the technology in the presence of the owner. This incentive payment, small from the point of view of the firm, had a significant positive effect on adoption. We interpret the results as supportive of the hypothesis that misalignment of incentives within firms is an important barrier to technology adoption in our setting.

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[†]Yale University, Dept. of Economics. E-mail: david.atkin@yale.edu
[‡]Lahore School of Economics. E-mail: azam@lahoreschool.edu.pk
[§]Lahore School of Economics. E-mail: shamyla@lahoreschool.edu.pk
[¶]Columbia Graduate School of Business. E-mail: ak2796@columbia.edu
[‖]Columbia University, Dept. of Economics and SIPA. E-mail: eric.verhoogen@columbia.edu

1 Introduction

Observers of the process of technological diffusion have been struck by how slow it is for many technologies.[1] A number of the best-known studies have focused on agriculture or medicine,[2] but diffusion has also been observed to be slow among large firms in manufacturing. In a classic study of major industrial technologies, for instance, Edwin Mansfield found that it took more than 10 years for half of major U.S. iron and steel firms to adopt by-product coke ovens or continuous annealing lines.[3] More recently, Bloom, Eifert, Mahajan, McKenzie, and Roberts (2013) found that many Indian textile firms are not using standard (and apparently cheap to implement) management practices that have diffused widely elsewhere. The surveys by Stoneman (2002), Hall and Khan (2003) and Hall (2005) contain many more examples.

Why is adoption so slow for so many technologies? The question is key to understanding the process of economic development and growth. It is also a difficult one to study, especially among manufacturing firms (Tybout, 2000). It is rare to be able to observe firms' technology use directly, and rarer still to have direct measures of the costs and benefits of adoption, or of what information firms have about a given technology. As a consequence, it is difficult to distinguish between various possible explanations for low adoption rates.

In this paper, we present evidence from a cluster of soccer-ball producers in Sialkot, Pakistan, that a conflict of interest between employees and owners within firms is an important barrier to adoption. The cluster produces 30 million soccer balls a year, or about 40 percent of world production, including match balls for the 2014 World Cup, and about 70 percent of world hand-stitched production (Wright, 2010; Houreld, 2014). The setting has two main advantages for understanding the adoption process. The first is that the industry is populated by a substantial number of firms — 135 by our initial count — producing a relatively standardized product and using largely the same, simple production process. The technology we focus on is applicable at a large enough number of firms to conduct statistical inference.

The second, and perhaps more important, advantage is that our research team, through a series of fortuitous events, discovered a useful innovation: we invented a new technology that represents, we argue, an unambiguous increase in technical efficiency for nearly all firms in the sector. The most common soccer-ball design combines 20 hexagonal and 12 pentagonal panels (see Figure 1). The panels are cut from rectangular sheets of an artificial leather called rexine, typically by bringing a hydraulic press down on a hand-held metal die. Our new technology, described in more detail below, is a die that increases the number of pentagons that can be cut

[1]For instance, in a well-cited review article, Geroski (2000) writes: "The central feature of most discussions of technology diffusion is the apparently slow speed at which firms adopt new technologies" (p. 604). See also Rosenberg (1982).

[2]See, for instance, Ryan and Gross (1943), Griliches (1957), Coleman and Menzel (1966), Foster and Rosenzweig (1995), and Conley and Udry (2010).

[3]See Mansfield (1961) and the summary in Table 2 of Mansfield (1989).

from a rectangular sheet, by implementing the best packing of pentagons in a plane known to mathematicians. A conservative estimate is that the new die reduces rexine costs for pentagons by 6.25 percent and reduces total costs by approximately 1 percent — a modest reduction but not an insignificant one in an industry where mean profit margins are 8 percent. The new die requires minimal adjustments to other aspects of the production process. Importantly, we observe adoption of the new die very accurately, in contrast to studies that infer technology adoption from changes in residual-based measures of productivity such as those reviewed in Syverson (2011).

We randomly allocated the new technology to a subset of 35 firms (which we refer to as the "tech drop" group) in May 2012. To a second group of 18 firms (the "cash drop" group) we gave cash equal to the value of the new die (US$300), and to a third group of 79 firms (the "no drop" group) we gave nothing. We initially expected the technology to be adopted quickly by the tech-drop firms, and we planned to focus on spillovers to the cash-drop and no-drop firms and the channels through which they operate; we pursue this line of inquiry in a companion paper (Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen, 2014). In the first 15 months of the experiment, however, the most striking fact was how few firms had adopted, even among the tech-drop group. As of August 2013, five firms from the tech-drop group and one from the no-drop group had used the new die to produce more than 1,000 balls in the previous month, our preferred measure of adoption. The experiences of the adopters indicated that the technology was working as expected; we were reassured, for instance, by the fact that the one no-drop adopter was one of the largest firms in the cluster, and had purchased a total of 32 dies on 9 separate occasions. Overall, however, adoption remained puzzlingly low.

In our April 2013 survey round, we asked non-adopters in the tech-drop group why they had not adopted. Of a large number of possible responses, the leading answer was resistance from cutters. Anecdotal evidence from a number of firms we visited suggested that workers were resisting the new die, including by misinforming owners about the productivity benefit of the die. We also noticed that the large adopter (purchaser of the 32 dies) differed from the norm for other firms in its pay scheme: while more than 90 percent of firms pay a pure piece rate, it pays a fixed monthly salary plus a performance bonus.

The qualitative evidence led us to hypothesize that *a misalignment of incentives within the firm* is an important reason for the lack of adoption. The new die slows cutters down, certainly in the initial period when they are learning how to use it, and possibly in the longer run (although our data suggest that the long-run speed is nearly the same as for the existing die). If cutters are paid a pure piece rate, their effective wage will fall in the short run. The new die requires a slight modification to another stage of production, printing, and printers face a similar but weaker disincentive to adopt. Unless owners modify the payment scheme, the benefits of using the new technology accrue to owners and the costs are borne by the cutters and printers.

Realizing this, the workers resist adoption. We formalize this intuition in a simple model of strategic communication between an imperfectly informed principal and a perfectly informed agent within a firm. When standard piece-rate contracts are used, there is an equilibrium in which the agent misinforms the principal about the benefits of the new technology and the principal is influenced by the agent not to adopt it. A relatively simple modification to the labor contract, conditioning the wage contract on marginal cost, an ex-post-revealed characteristic of the technology, induces the agent to truthfully reveal the technology and the principal to adopt it.

To investigate the misalignment-of-incentives hypothesis, we designed and implemented a new experiment. In September 2013, we randomly divided the set of 31 tech-drop firms that were still in business into two groups, a treatment group (which we call the A group) and a control group (the B group).[4] To the B group, we simply gave a reminder about the benefits of the die and an offer of another demonstration of the cutting pattern. To the A group, we gave the reminder but also explained to the owner the issue of misaligned incentives and offered an incentive-payment treatment: we offered to pay one cutter and one printer a lump-sum bonus roughly equivalent to a monthly wage (US$150 and US$120, respectively), conditional on demonstrating competence with the new technology (in the presence of the owner) within one month. This bonus was designed to mimic (as closely as possible, given firms' reluctance to participate) the modified "conditional" wage contracts we model in the theory. The one-time bonus payments were small relative both to revenues from soccer-ball sales for the firms, which have a mean of approximately US$146,000 and a median of approximately US$58,000 per month, and to the (variable) cost reductions from adopting of our technology, which we estimate to be approximately US$1,740 per month at the mean or US$493 per month at the median.

The incentive-payment experiment was run on a total of 31 firms, 15 in group A and 16 in group B. Of the 13 group-A firms that had not already adopted the new die, 8 accepted the incentive-payment intervention, and 5 subsequently adopted the new die. Of the 13 group B firms that had not already adopted the new die, none subsequently adopted. Although the sample size is small, the positive effect on adoption is statistically significant, with the probability of adoption increasing by 0.32 from a baseline adoption rate of 0.16 in the most conservative intent-to-treat specification. Our results remain significant when using permutation tests that are robust to small sample sizes. The fact that such small payments had a significant effect on adoption suggests that the misalignment of incentives is indeed an important barrier to adoption in this setting. In contrast, we find no support for a related hypothesis, that our incentive payment simply subsidized the fixed costs of adoption, since such a hypothesis cannot plausibly generate the adoption rates we find.

[4] Of the original 35 tech-drop firms, 4 were no longer producing soccer balls as of August 2013 leaving 31 tech-drop firms for the new experiment.

A natural question is why the firms themselves did not adjust their payment schemes to incentivize their employees to adopt the technology. Our model suggests two possible explanations. The first is that owners simply did not realize that such an alternative payment scheme was possible, just as the technical innovation had not occurred to them. The second is that there is some sort of transaction cost involved in changing payment schemes, a possibility that we discuss in more detail in Section 6 below. Firms weigh the perceived benefits of the technology against the transaction cost; if they have a low prior that the technology is beneficial, they may not be willing to pay the cost. The hypotheses that firms were unaware of the alternative payment scheme and that implementing a new scheme was perceived to be too costly to be worthwhile have similar observable implications and we are not able to separate them with our second experiment. What is clear, however, is that many firms did not in fact adjust the payment scheme, and for that reason there was scope for our modest payment intervention to have a positive effect on adoption.

In addition to the research cited above, our paper is related to several different strands of literature. A number of papers have highlighted resistance to adopting new technologies in manufacturing. Lazonick (1979) and Mokyr (1990) argue that guilds and trade unions slowed implementation of new technologies during the industrial revolution; Desmet and Parente (forthcoming) further suggest that this was due to small markets and lack of competition. Similarly, Parente and Prescott (1999) argue that monopoly rights in factor supplies can explain low levels of adoption. Historically, many cases are of resistance to labor-saving technologies that could substitute for the labor of skilled artisans. Focusing on more recent periods, Bloom and Van Reenen (2007, 2010) and the aforementioned Bloom et al. (2013) suggest that a lack of competition may be responsible to the failure to adopt beneficial management practices. Another literature emphasizes that new technologies often require changes in complementary technologies, which take time to implement (Rosenberg, 1982; David, 1990; Bresnahan and Trajtenberg, 1995). In our setting, unions are absent, firms sell almost all output on international export markets that appear to be quite competitive, and our technology is *labor-using* rather than labor-saving and requires extremely modest changes to other aspects of production, so it does not appear that the most common existing explanations are directly applicable. We view our focus on intra-organizational barriers as complementary to these literatures.

The theoretical model we develop draws on ideas from two strands of theoretical research: the literature on strategic communication following Crawford and Sobel (1982) and the voluminous literature on principal-agent models of the employment relationship reviewed by Lazear and Oyer (2013) and Gibbons and Roberts (2013). There is a smaller literature that combines elements of the two strands, for instance Lazear (1986), Gibbons (1987), Dearden, Ickes, and Samuelson (1990), Carmichael and MacLeod (2000), Dessein (2002) and Krishna and Morgan (2008). Lazear (1986) and Gibbons (1987) formalize the argument that workers paid piece rates may hide information about productivity improvements from their employers, to prevent employers from reducing rates. Carmichael and MacLeod (2000) explore the contexts in which firms will commit to fixing piece rates in order to alleviate these "ratchet" effects. Holmstrom and Milgrom (1991) show that high-powered incentives such as piece rates may induce employees to focus too much on the incentivized task to the detriment of other tasks, which could include reporting accurately on the value of a technology. Our study supports the argument of Milgrom and Roberts (1995) that piece rates may need to be combined with other incentives, in our case higher pay conditional on adopting the new technology. In related empirical work, Freeman and Kleiner (2005) provide case-study evidence from an American shoe company whose shift away from piece rates arguably helped it to increase productivity.[5]

Our paper is related to an active literature on technology adoption in non-manufacturing settings in developing countries. Much of this work has focused on agriculture, where clean measures of technology use are more often available than in manufacturing (e.g. Foster and Rosenzweig (1995), Munshi (2004), Bandiera and Rasul (2006), Conley and Udry (2010), Duflo, Kremer, and Robinson (2011), Suri (2011), Hanna, Mullainathan, and Schwartzstein (forthcoming), BenYishay and Mobarak (2014)). We believe that manufacturing firms are important in their own right, as their decisions clearly matter for development and growth. They also raise issues of organizational conflict that do not arise when the decision-makers are individual farmers. In addition, risk arguably plays a less important role among manufacturing firms than in many agricultural settings, both because there is a lower degree of production risk (which we would expect to make the inference problem about the value of a technology easier) and because factory owners are presumably less risk-averse than small-holder farmers. Also related are recent papers on adoption of health technologies in the presence of externalities (Miguel and Kremer, 2004; Cohen and Dupas, 2010; Dupas, 2014) and on the effect of informational interventions on change-holding behavior of Kenyan retail micro-enterprises (Beaman, Magruder, and Robinson, 2014). As with the literature on agriculture, in none of these settings does organizational conflict play an important role.

Our paper is also related to a small but growing literature on field experiments in firms, including the experiments with fruit-pickers by Bandiera, Barankay, and Rasul (2005, 2007, 2009) and the aforementioned study by Bloom et al. (2013) of the effect of management consulting services on productivity in the Indian textile industry.[6] In addition to emphasizing the lack of competition, Bloom et al. suggest that "informational constraints" are an important factor leading firms not to adopt simple, apparently beneficial, elsewhere widespread, practices. Our study

[5]Descriptive evidence on intra-organizational conflicts over piece rates is provided by the classic studies of Edwards (1979) and Clawson (1980). A recent experimental study by Khwaja, Olken, and Khan (2014) focuses on a public bureaucracy in the Punjab property tax department, but focuses on a similar issue: the effect of altering wage contracts on employee performance and resistance to reform.

[6]See Bandiera, Barankay, and Rasul (2011) for a review of the literature on field experiments in firms.

investigates how a conflict of interest within firms can impede the flow of information to managers and provides a possible microeconomic rationale for the importance of such informational constraints, and in this sense we view our work as complementary.[7]

The paper is organized as follows. Section 2 provides background on the Sialkot cluster. Section 3 describes the new cutting technology. Section 4 describes our surveys and presents summary statistics. Section 5 details the roll-out of the new technology and documents rates of early adoption. Section 6 discusses qualitative evidence on organizational barriers and presents our model of strategic communication in a principal-agent context. Section 7 describes the incentive-payment experiment and evaluates the results. Section 8 concludes.

2 Industry Background

Sialkot, Pakistan is a city of 1.6 million people in the province of Punjab. The origins of the soccer-ball cluster date to British colonial rule.[8] Soccer balls for British regiments were imported from England, but given the long shipping times, there was growing need to produce balls locally. In 1889, a British sergeant asked a Sialkoti saddle-maker to repair a damaged ball. The saddle-maker's new ball impressed the sergeant, who placed orders for more balls. The industry subsequently expanded through spinoffs from the original firm and new entrants. By the 1970s, the city was a center of offshore production for many European soccer-ball companies, and in 1982, firms in Sialkot manufactured the balls used in the FIFA World Cup for the first time.

Virtually all of Pakistan's soccer ball production is concentrated in Sialkot and exported to foreign markets. In recent years, the global market share of the cluster has been shrinking. Considering U.S. imports (for which, conveniently, there is a 10-digit Harmonized System category for inflatable soccer balls, 9506.62.40.80), Pakistan's market share fell from a peak of 71 percent in 1996 to 17 percent in 2012. In contrast, China's market share rose from 19 percent to 71 percent over the same period. (See Figure 2.) The firms in Sialkot face increasing pressure from Chinese producers at both the high and low ends of the soccer ball market. At the low end, China dominates production of lower-quality machine-stitched balls. At the high end, Chinese firms manufacture the innovative thermo-molded balls that have been used in recent FIFA World Cups (with the balls the 2014 FIFA World Cup being made in both China and Sialkot). Sialkot still remains the major source for the world's hand-stitched soccer balls; it provided, for example, the hand-stitched balls used in the 2012 Olympic Games.

[7] In other related work on firms, Anderson and Newell (2004) study the effect of information from energy-efficiency audits on U.S. firms' adoption decisions in a non-experimental setting. The paper does not focus on the role of organizational barriers. The "insider econometrics" literature reviewed by Ichniowski and Shaw (2013) focuses on relationships between management practices and productivity, typically in a cross-sectional context.

[8] This summary of the history of the sector draws on an undated, self-published book by a member of a soccer-ball-producing family (Sandal, undated).

To the best of our knowledge, there were 135 manufacturing firms producing soccer balls in Sialkot as of November 2011. The firms themselves employ approximately 12,000 workers, and outsourced employment of stitchers in stitching centers and households is generally estimated to be more than twice that number (Khan, Munir, and Willmott, 2007). The largest firms have hundreds of employees (the 90th percentile of firm size among our sample is 225 employees) and typically produce for large international sports brands such as Nike and Adidas as well as under their own brands or for smaller country-specific brands. These firms manufacture both high-quality "match" and medium-quality "training" balls, often with a sports brand or soccer team's logo, as well as lower quality "promotional" balls, often branded with an advertiser's logo. The remaining producers in our sample are small- and medium-size firms (the median firm size is 16 employees) who typically produce promotional balls either for clients met at industry fairs and online markets or under subcontract to larger firms.

3 The New Technology

3.1 Description

Before presenting our new technology, we first briefly explain the standard production process. As mentioned above, most soccer balls (approximately 90 percent in our sample) are of a standard design combining 20 hexagons and 12 pentagons (see Figure 1), often referred to as the "buckyball" design.[9] There are four stages of production. In the first stage, shown in Figure 3, layers of cloth (cotton and/or polyester) are glued to an artificial leather called rexine using a latex-based adhesive, to form what is called a laminated sheet. The rexine, cloth and latex are the most expensive inputs to production, together accounting for approximately 46 percent of the total cost of each soccer ball (or more if imported rexine, which is higher-quality, is used instead of Pakistani rexine). In the second stage, shown in Figure 4, a skilled cutter uses a metal die and a hydraulic press to cut the hexagonal and pentagonal panels from the laminated sheets. The cutter positions the die on the laminated sheet by hand before activating the press with a foot-pedal. He then slides the laminated sheet along and places the die again to make the next cut.[10] In the third stage, shown in Figure 5, logos or other insignia are printed on the panels. This requires designing a "screen," held in a wooden frame, that allows ink to pass through to create the desired design. Typically the cutting process produces pairs of hexagons or pentagons that are not completely detached; the die makes an indentation but leaves them attached to be printed as a pair, using one swipe of ink. In the fourth stage, shown in Figure 6, the panels are stitched together around an inflatable bladder. Unlike the previous three stages, this stage

[9] The buckyball resembles a geodesic dome designed by R. Buckminster Fuller.

[10] We use "he" since all of the cutters (as well as the printers and owners) we have encountered in the industry have been men.

is often outsourced, with stitching taking place at specialized stitching centers or in stitcher's homes. The production process is remarkably similar across the range of firms in Sialkot. A few of the larger firms have automated the cutting process, cutting half-sheets or full sheets of rexine at once, or attaching a die to a press that moves on its own, but even these firms typically continue to do hand-cutting for a substantial share of their production. A few firms in the cluster have implemented machine-stitching, but this has little effect on the first three stages of production.

Prior to our study, the most commonly used dies cut two panels at a time, either two hexagons or two pentagons, with the two panels sharing an entire edge (Figure 7). Hexagons tessellate (i.e. completely cover a plane), and experienced cutters are able to cut with a small amount of waste — approximately 8 percent of a laminated sheet, mostly around the edges. (See the rexine "net" remaining after cutting hexagons in Figure 8.) Pentagons, by contrast, do not tessellate, and using the traditional two-pentagon die even experienced cutters typically waste 20-24 percent of the laminated sheet (Figure 9). The leftover rexine has little value; typically it is sold to brickmakers who burn it to fire their kilns.

In June 2011, as we were first exploring the possibility of studying the soccer-ball sector, we sought out a consultant who could recommend a beneficial new technique or practice that had not yet diffused in the industry. We found a Pakistan-based consultant who appears to have been responsible for introducing the existing two-hexagon and two-pentagon dies many years ago. (Previously firms had used single-panel dies.) We offered the consultant US$4,125 to develop a cost-saving innovation for us. The consultant spent several days in Sialkot but was unable to improve on the existing technology. After this setback, a co-author on this project, Eric Verhoogen, happened to watch a YouTube video of a Chinese firm producing the Adidas "Jabulani" thermo-molded soccer ball used in the 2010 FIFA World Cup. The video showed an automated press cutting pentagons for an interior lining of the Jabulani ball using a pattern different from the one we knew was being used in Sialkot (Figure 10). Based on the pattern in the video, Verhoogen and his wife, Annalisa Guzzini, an architect, developed a blueprint for a four-pentagon die (Figures 11 and 12). Through an intermediary, we then contracted with a diemaker in Sialkot to produce the die (Figure 13). It was only after we had received the first die and piloted it with a firm in Sialkot that we discovered that the cutting pattern is well known to mathematicians. The pattern appeared in a 1990 paper in the journal *Discrete & Computational Geometry* (Kuperberg and Kuperberg, 1990).[11] It also appears, conveniently enough, on the Wikipedia "Pentagon" page (Figure 14).[12]

[11] The cutting pattern represents the best known packing of regular pentagons into a plane. Kuperberg and Kuperberg (1990) conjecture that the pattern represents the densest possible packing, but this is not a theorem.

[12] One might wonder whether firms in Sialkot also observed the production process in the Chinese firm producing for Adidas, since it was so easy for us to do so. We found one owner, of one of the larger firms in Sialkot, who said that he had been to China and observed the offset cutting pattern (illustrated in Figure 11) and was planning to

The pentagons in the new die are offset, with the two leftmost pentagons sharing half an edge, unlike in the traditional two-pentagon die in which the pentagons are flush, sharing an entire edge. We refer to the new die as the "offset" die, and treat other dies with pentagons sharing half an edge as variations on our technology. Note that a two-pentagon variant of our design can easily be made using the specifications in the blueprint (with the two leftmost and two rightmost pentagons in Figure 12 cut separately). As we discuss in more detail below, the two-pentagon offset die is the one that has proven more popular with firms.

3.2 Benefits and costs

We now turn to a calculation of the benefits and costs of using the new offset die. In order to quantify the various benefit and cost components we draw on several rounds of survey data that we describe in more detail in Section 4 below.

3.2.1 Reductions in wastage

We start by comparing the number of pentagons using the traditional die with the number using the offset die. The dimensions of pentagons and hexagons vary slightly across firms, even for balls of a given official size (e.g. size 5, the standard size for adults). The most commonly used pentagons have edge-length 43.5 mm, 43.75 mm, 44 mm or 44.25 mm after stitching. The first two columns of Table 1 report the means and standard deviations of the numbers of pentagons per sheet for each size, using a standard (39 in. by 54 in.) sheet of rexine. Column 1 uses information from owner self-reports; we elicited the information in more than one round, and here we pool observations across rounds. Column 2 uses information from direct observation by our survey team, during the initial implementation of our first experiment. In order to facilitate comparison across die sizes, we have multiplied each size-specific measure by the ratio of means for size 44 mm and the corresponding size, and then averaged the rescaled measure across sizes. The rescaled measure, reported in the row labeled "rescaled," provides an estimate of the number of pentagons per sheet the firm would obtain if it used a size 44 mm die. We see that the owner reports and direct observations correspond reasonably closely, with owners slightly overestimating pentagons per sheet relative to our observations. Both measures suggest that cutters obtain approximately 250 pentagons per sheet using the traditional die.

Using the new offset die and cutting 44 mm pentagons, it is possible to achieve 272 pentagons,

implement it on a new large cutting press to cut half of a rexine sheet at once, a process known as "table cutting". As of May 2012, he had not yet implemented the new pattern, however, and he had not developed a hand-held offset die. It is also important to note that two of the largest firms in Sialkot have not allowed us to see their production processes. As these two firms are known to produce for Adidas, we suspect that they were aware of the offset cutting pattern before we arrived. What is clear, however, is that neither the offset cutting pattern nor the offset die were in any other firm we visited as of the beginning of our experiment in May 2012.

as illustrated in Figure 11.[13] For smaller 43.5 mm pentagons, it is possible to achieve 280 pentagons. Columns 3-4 of Table 1 report the means and standard deviations of pentagons per sheet using the offset die. As discussed in more detail below, relatively few firms have adopted the offset die, and therefore we have many fewer observations. But even keeping in mind this caveat, we can say with a high level of confidence that more pentagons can be obtained per sheet using the offset die. The directly observed mean is approximately 272, and the standard errors indicate that difference from the mean for the traditional die (either owner reports or direct observations) is significant at greater than the 99 percent level.

3.2.2 Cost savings from reduced wastage

In order to convert these reductions in wastage into cost savings we need to know the proportion of costs that materials and cutting labor account for. Table 2 provides a cost breakdown for a promotional ball obtained from our baseline survey.[14] The table shows that the laminated sheet (which combines the rexine and cotton/polyester cloth using the latex glue) accounts for roughly half of the unit cost of production: 46 percent on average. The inflatable bladder is the second most important material input, accounting for 21 percent of the unit cost. Labor of all types accounts for 28 percent, but labor for cutting makes up less than 1 percent of the unit cost. Overhead accounts for the remaining 5 percent of the cost of a ball. In the second column, we report the input cost in rupees; the mean cost of a two-layer promotional ball is Rs 211. (The exchange rate has varied from 90 Rs/US$ to 105 Rs/US$ over the period of the study. To make calculations easy, we will use an exchange rate of 100 Rs/US$ hereafter.)

The cost savings from the offset die vary across firms, depending in part on the type of rexine used and the number of layers of cloth glued to it, which themselves depend on a firm's mix of promotional balls and more expensive training balls. How long it takes firms to recoup the fixed costs of adoption also varies across firms, depending on total production and the number of cutters employed by the firm, in addition to the reduction in variable costs.[15] In Table 3, we present estimates of the distribution of the benefits and costs of adopting the offset die for firms. Not all firms were willing to provide a cost breakdown by input in the baseline survey, and only a subset of firms have adopted the offset die. In order to compute the distribution of costs of benefits across all firms, we adopt a hot-deck imputation procedure that replaces a firm's missing value for a particular cost component with a draw from the empirical distribution within

[13] If a cutter reduces the margin between cuts, or if the rexine sheet is slightly larger than 39 in. by 54 in., it is possible to cut more than 272 with a size 44 mm die.

[14] In the baseline survey, firms were asked for a cost breakdown of a size-5 promotional ball with two layers (one cotton and one polyester), the rexine they most commonly use on a two-layer size-5 promotional ball, a glue comprised of 50 percent latex and 50 percent chemical substitute (a cheaper alternative), and a 60-65 gram inflatable latex bladder.

[15] Some firms have multiple cutters each of whom may require his own die.

the firm's stratum, and then compute the distribution of benefits.[16] We repeat this procedure 1,000 times and report the mean values and standard deviations at various percentiles of the distribution.

In row 1 of Table 3, we report the distribution of the percentage reduction in rexine waste from the offset die. This is the product of (a) the percentage decline in rexine waste in cutting pentagons from adopting the offset die, (b) the share of pentagons in total rexine costs (about 33 percent because a standard ball uses more hexagons than pentagons and each hexagon has a larger surface area than each pentagon), and (c) the share of rexine in unit costs. The reduction in rexine waste is 7.93 percent at the median and ranges from 4.39 percent at the 10th percentile to 13.43 percent at the 90th percentile. Combining the reduction in rexine waste with the rexine share of unit costs (which has the distribution is reported in row 2) and multiplying by 33 percent yields the percentage reduction in variable material costs reported in row 3. The reduction in variable material costs is 1.10 percent at the median and ranges from .60 percent at the 10th percentile to 1.94 at the 90th percentile.[17]

The new die requires the cutters to be more careful in the placement of the die while cutting. A conservative estimate of the increase in labor time for cutters is 50 percent. (Below we discuss why this number is conservative.) The fourth row of Table 3 reports the distribution of the cutter's wage as a share of unit costs across firms. As noted earlier, the cutter's share of cost is quite low.[18] Multiplying the cutter share by 33 percent (assuming that pentagons take up one third of cutting time, equivalent to their share of rexine cost) and then by 50 percent (an estimate of the increase in labor time) yields the percentage increase in variable labor costs from adopting the offset die (row 5).

Although the proportional increase in cutting time is potentially large, the cutter's share of cost is sufficiently low that the variable labor cost increase is very small. Row 6 reports the *net* variable cost reduction as the difference between the variable materials cost reduction and the variable labor cost increase. The net variable cost reduction is 1.02 percent at the median, and

[16]As discussed below, firms were stratified according to total monthly output (measured in number of balls) at baseline. One stratum, the late-responder sample we describe in detail below, did not respond to the baseline survey. Because information on rexine shares were collected only at baseline, we draw rexine shares for late responders from the empirical distribution that pools the other strata. (We do not pool for the other variables, for which we have information on the late responders from later rounds.

[17]Note that because a firm at the 10th percentile of rexine waste reduction is not necessarily the same firm at the 10th percentile of rexine as a share of cost, the numbers are not multiplicative across rows within a percentile. Likewise, the mean of the variable material cost reduction is not multiplicative across rows because of potential correlations between rexine as a share of costs and rexine waste reduction.

[18]The cutter wage as a share of costs reported here is lower than in Table 2. This is because Table 2 reports input components as a share of the cost of a promotional ball. In Table 3, we explicitly account for firms' product mix across promotional and training/match balls. To get the firm's average ball cost, we divide its reported price of a promotional ball by one plus the reported promotional-ball profit margin. We perform the analogous procedure for training balls, which are more expensive to make. We then construct the firm's weighted-average unit cost using its reported fraction of total production on promotional balls. The cutter share of cost is then calculated as the per ball payment divided by this weighted-average unit cost.

ranges from .52 percent at the 10th percentile to 1.87 percent at the 90th percentile. Although these numbers are small in absolute terms, the cost reductions are not trivial given the low profit margins in this competitive industry. Row 7 shows the ratio of the net variable cost reductions to average profits;[19] the mean and median ratios are 15.45 percent and 12.34 percent, respectively, and the ratio ranges from 5.27 percent at the 10th percentile to 28.98 percent at the 90th percentile.

If we multiply the net variable cost reduction by total monthly output, we obtain the total monthly savings, in rupees, from adopting the offset die (row 8). The large variation in output across firms induces a high degree of heterogeneity in total monthly cost savings. The mean and median monthly cost savings are Rs 174,120 (US$1,741) and Rs 49,380 (US$493), respectively, and savings range from Rs 4,460 (US$44) at the 10th percentile to Rs 475,010 (US$4,750) at the 90th percentile.

3.2.3 Net benefits of adoption

These reductions in variable cost must be compared with the fixed costs of adopting the offset die. There are a number of such costs, but they are modest in monetary terms. First, the firm must purchase the die itself. We were charged Rs 30,000 (US$300) for a four-piece die; the market price for a two-pentagon offset die is now about Rs 10,000 ($100). As we explain below, we paid this fixed cost for the firms in the tech-drop group, to which we gave the new die initially. Second, the existing screens used to print logos and branding on the panels must be re-designed and re-made to match the offset pattern. Designers typically charge Rs 600 (US$6) for each new design; for the minority of firms that do not have in-house screenmaking capabilities, a new screen costs Rs 200 ($2) to buy from an outside screenmaker. We note that new screens must in any case be made for any new order but we include them to be conservative. Third, some firms use a hole-punching machine, a device that punches holes at the edges of panels to facilitate sewing. These machines also use dies. It is always possible to use a single-pentagon punching die, but there is a speed benefit to using a two-pentagon punching die in these machines. A two-pentagon punching die that works with pentagons cut by the two-pentagon offset die costs approximately Rs 10,000 (US$100). Adding together these three components, a conservative estimate of total fixed costs is Rs 20,800 (US$208).

A common way for firms to make calculations about the desirability of adoption is to use a rule of thumb (or "hurdle") for the length of time required to recoup the fixed costs of adoption (the "payback period"). Reviewing a variety of studies from the U.S. and U.K., Lefley (1996) reports that the "hurdles" vary from 2-4 years, with the mean at approximately 3 years.[20]

[19] The firm's profit margin is a weighted average of its reported profit margin on promotional and training balls where the weights are the share of each ball type in total production.

[20] Using data from energy-efficiency audits in the U.S., Anderson and Newell (2004) infer that firms are using hurdles of 1-2 years.

The final two rows of Table 3 report the distribution of the number of days needed to recover the fixed costs of adoption detailed above. For this calculation, it is important to account for the fact that firms often have multiple cutters, each of whom may have his own pentagon die (and potentially need a separate screen and punch). We divide monthly firm output by the number of cutters to calculate output per cutter per month and hence the cost savings per cutter per month. Dividing our conservative estimate of (per cutter) fixed costs by cost savings per cutter gives the number of days needed to recoup the fixed costs, reported in row 9. The median firm can recover all fixed costs within 37 days; the payback period ranges from 9 days at the 10th percentile to 194 days at the 90th percentile (which corresponds to firms that produce very few balls). The final row reports the distribution of days to recover fixed costs that exclude the cost of purchasing the die; this row is relevant for the tech-drop firms, to which we gave dies at no cost. In this scenario, the median days to recover fixed costs is only 19 days.

3.2.4 Advantages of the technology for studying adoption

The setting and our technology have a number of advantages for the purpose of studying adoption. First, virtually all firms in the cluster cut hexagons and pentagons in the manner described above, at least for some portion of their production. Second, it is straightforward to measure whether firms are using the technology, either by observing the cutters directly or by inspecting the discarded rexine nets. We have also obtained reports of sales of the offset dies from the six diemakers operating in Sialkot. Third, as detailed above, the new die requires minimal changes to other aspects of production. Fourth, the new technology is easy to disseminate. It can be explained and demonstrated in thirty minutes. Finally, from the cost calculations above, it seems clear that the net benefits of the technology are positive for any firm expecting to produce more than an extremely modest number of balls. In 75 percent of firms, the fixed costs of adoption could be paid off in less then three months. For half of the firms, it would take less than 5 weeks. For the subset of firms to which we gave dies, the corresponding numbers are 5 weeks and 3 weeks.

4 Data and Summary Statistics

Between September and November of 2011, we conducted a listing exercise of soccer-ball producers within Sialkot. We found 157 producers that we believed were active in the sense that they had produced soccer balls in the previous 12 months and cut their own laminated sheets. Of the 157 firms on our initial list, we subsequently discovered that 22 were not active by our definition. Of the remaining 135 firms, 3 served as pilot firms for testing our technology.

We carried out a baseline survey between January and April 2012. Of the 132 active non-pilot firms, 85 answered the survey; we refer to them as the "initial responder" sample. The low response rate was in part due to negative experiences with previous surveyors.[21] In subsequent survey rounds our reputation in Sialkot improved and we were able to collect information from an additional 31 of the 47 non-responding producers (the "late responder" sample), to bring the total number of responders to 116. The baseline collected firm and owner characteristics, standard performance variables (e.g. output, employment, prices, product mix and inputs) and information about firms' networks (supplier, family, employee and business networks). To date, we have conducted seven subsequent survey rounds, in May-June 2012, July 2012, October 2012, January 2013, March-April 2013, September-November 2013 and January-March 2014. The follow-up surveys have again collected information on the various performance measures as well as information pertinent to the adoption of the new cutting technology.

Table 4 presents summary statistics on various firm characteristics, including means and values at several quantiles. Panel A reports statistics for the sample of 85 baseline responders and Panel B for the full sample that also includes the 31 late responders. Because the late responders did not respond to the baseline, we have a smaller set of variables for the full sample. As firms' responses are often noisy, where possible we have taken within-firm averages across all survey rounds for which we have responses (indicated by "avg. ..." at the beginning of variable names in the table). Focusing on the initial-responder sample, a number of facts are worth emphasizing. The median firm is medium-size (20 employees, producing 10,000 balls/month) but there are also some vary large firms (maximum employment is 1,700, producing nearly 300,000 balls per month).[22] Profit rates are generally low, approximately 8 percent at the median and 12.5 percent at the 90th percentile. The corresponding firm size and profit margins in the full sample (Panel B) are slightly larger indicating that the late responders are larger than the initial responders. For most firms, all or nearly all of their production of size-5 balls uses the standard "buckyball" design. The industry is relatively mature; the mean firm age is 25.4 years, 19.5 years at the median and 54 years at the 90th percentile. Finally, cutters tend to have high tenure; the mean tenure in the current firm for a head cutter is approximately 11 years (9 years at the median). One other salient fact is that the vast majority of firms pay pure piece rates to their cutters and printers. Among the initial responders, 77 of 85 firms pay a piece rate to their cutters, with the remainder paying a daily, weekly or monthly salary and possibly performance bonuses.[23] Table A.1 in the appendix shows how the same variables very across firm-size bins for both the initial-responder and full samples.

[21] In 1995, there was a child-labor scandal in the industry in Sialkot. Firm owners were initially quite distrustful of us in part for that reason.

[22] The employment numbers understate the true size of the industry since the most labor intensive stage of production, stitching, is almost exclusively done outside of the firm in stitching centers or homes.

[23] In a later survey round, we also found that more than 90 percent of firms pay their printers a piece rate.

5 Experiment 1: The Technology-Drop Experiment

In this section we briefly describe our first experiment, the technology-drop experiment. Additional details are provided in Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2014), which focuses on spillovers in technology adoption. For the purposes of the current paper, the first experiment mainly serves to provide evidence of low adoption, a puzzle we investigate using the second experimental intervention motivated in Section 6 and described in Section 7.

5.1 Experimental design

The 85 firms in the initial-responder sample were divided into four strata based on quartiles of the number of balls produced in a normal month from the baseline survey. Within these strata firms were randomly assigned to one of three groups: the tech-drop group, the cash-drop group, and the no-drop group. We included the cash-drop group in order to shed light on the possible role of credit constraints in the technology-adoption decision.[24] The top panel of Table 5 summarizes the distribution of firms across groups for the initial-responder sample. Approximately 27 percent of firms were assigned to the tech-drop group and 13.5 percent to the cash-drop group.[25] These allocations were chosen with the aim of ensuring we had a sufficient number of firms outside the tech-drop group to examine the channels through which spillovers occur. In addition, because we were interested in tracking all firms in the cluster, we treated initial non-responders as a separate stratum and divided them into three groups using the same proportions as for the initial responders. Of the initial non-responders, 22 were revealed not to be active firms. Of the remaining 47 firms, 31 eventually responded to at least one of our survey rounds; these are the "late responders" included in the full sample discussed in Section 4. The bottom panel of Table 5 summarizes the response rates for the initial non-responders. It is important to note that response rates of the active initial non-responders are clearly correlated with treatment assignment: firms assigned to the tech-drop and cash-drop groups (to which we were giving the new die or cash, as described below) were more likely to respond than firms assigned to the no-drop group. For this reason, when it is important that assignment to treatment in the tech-drop experiment be exogenous, we will focus on the initial-responder sample. In our second experiment, where we focus only on active tech-drop firms, all of which

[24] In an experiment with micro-enterprises in Sri Lanka, de Mel, McKenzie, and Woodruff (2008) find very high returns — higher than going interest rates — to drops of cash or capital of roughly similar magnitudes (US$100 or US$200), suggesting that the micro-enterprises operate under credit constraints. Although our prior was that the US$300 value of the new die would matter less to the larger firms in our sample, we chose to include the cash-drop component in order to be able to separate the effect of the shock to capital from the effect of knowledge about the technology.

[25] There were 88 firms with 22 in each stratum at the moment of assignment. In each stratum, 6 firms were assigned to the tech-drop group, 3 to cash-drop group and 13 to the no-drop group. Three firms that responded to our baseline survey subsequently either shut down or were revealed not to be firms by our definition, leaving 85 firms.

responded, this distinction will be irrelevant.

We began the technology-drop experiment in May 2012. Firms assigned to the technology group were provided with a four-pentagon offset die, along with a blueprint that could be used to modify the die (combining Figures 11 and 12). Additionally, these firms were given a thirty-minute demonstration of the cutting pattern for the new die. The die we provided cuts pentagons with edge-length of 44 mm. As noted in Section 3 above, firms often use slightly different size dies, and the pentagon die size must match the hexagon die size. For this reason, we also offered firms a free trade-in: we offered to replace the die we gave them with an offset die of a different size, produced at a local diemaker of their choice. Firms were also able to trade in their die for a two-panel version of the offset die of the same size. Of the 35 tech-drop firms, 19 took up the trade-in offer. All of these chose to trade in for the two-panel version of the offset die. The two-panel version is easier to maneuver with one hand and as a consequence the cutting rhythm with the two-panel offset die is more similar to the rhythm using the two-panel traditional die. The cash group was given cash equal to the price we paid for each four-pentagon offset die, Rs 30,000 (US$300), but no information about the new die. Firms in the no-drop group were given nothing.

To examine baseline balance, Panel A of Table 6 reports the mean of various firm characteristics across the tech-drop, cash-drop and no-drop groups for the initial-responder sample. We find no significant differences across groups.[26] It appears that the randomization generated exogenous variation in initial exposure among the initial responders. Panel B of Table 6 reports the analog for the 31 late responders. Here we see significant differences for various variables, consistent with the observation above that response rates among the late responders appear to have responded endogenously to treatment assignment. Caution is clearly warranted in interpreting results that include the late responders.

5.2 Early adoption of the new technology

We have continued to monitor closely the technology use of all firms in the cluster, in addition to other variables.[27] In tech-drop group firms, we have explicitly asked about usage of the offset die. For the other groups, we have sought to determine whether firms are using the offset die without explicitly mentioning the offset die, through four methods. First, in our surveys we asked whether the firm recently adopted any new technologies or production processes. If they reported adopting a new cutting technology, we asked them to describe it further. Second, we asked for the number of pentagons cut per sheet and queried further if these numbers had risen from previous rounds. Third, our survey team was attentive to any mention of the offset die in the factory,

[26] On average, firms in the technology group employ fewer people than other firms, but the differences are not statistically different at the 5 percent level.

[27] The timing of the survey rounds appears in Section 4.

whether or not in the context of the formal survey. Fourth, we have maintained independent contact with the six diemakers in Sialkot, who have agreed to provide us information on sales of the offset die. Based on this information, we believe that we have complete knowledge of offset dies purchased in Sialkot, even by firms that have never responded to any of our surveys. Any firm who appears in the diemakers' registers as having received an offset die was asked directly about usage. If we had evidence that the firm adopted any variant of the offset die through any of the four sources above, we asked additional questions to learn more details about the adoption process and information flows pertaining to the die.

Table 7 reports adoption rates as of August 2013, 15 months after we introduced the technology, with the initial-responder sample in Panel A and the full sample in Panel B. The first three rows of each panel indicate the number of firms that were both active and responded to our surveys. The fourth row reports that a high proportion of tech-drop firms took up our offer of a trade-in for a different die. The fifth and sixth rows report the number of firms that ordered and that received dies (beyond the one trade-in offered to tech-drop firms). The numbers are modest: in the full sample, one tech-drop firm and six no-drop firms made an additional order. (One diemaker was slow in delivering dies and firms canceled their orders, hence the discrepancy between the fifth and sixth rows).

In measuring adoption of the technology, we face a choice about whether to require that the offset die was used in the production of some minimum number of balls and what bound to use. Several firms reported that they had experimented with the die but had not actually used it for a client's order. To be conservative, we have chosen not to count such firms as adopters. Our preferred measure of adoption requires that firms have produced at least 1,000 balls in the previous month with the offset die. The measure is not particularly sensitive to the lower bound; any bound above 100 balls would yield similar counts of adopters. Using our preferred measure of adoption, the seventh and eighth rows of Table 7 report the number of firms who had ever adopted the offset die and the number who were currently using the die in August 2013, respectively.

In the full sample, there were five adopters in the tech-drop group and one in the no-drop group as of August 2013.[28] (In the initial-responder sample, the corresponding numbers are four and zero.) These numbers struck us as small. Given the apparently clear advantages of the technology discussed above, we were expecting much faster take-up among the firms in the tech-drop group.

[28] Recall that only the technology group was provided with the technology, and so any adoption among the other two groups constitutes a spillover. Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2014) investigates spillovers and the channels through which they operate.

5.3 Examining alternative explanations for low adoption

In this sub-section, we examine several standard hypotheses that may explain limited adoption of the offset die as of Aug. 2013. We emphasize that this is primarily a descriptive exercise; we are not placing a causal interpretation on the correlations we observe in the data. Additionally, given the low rates of adoption, we have limited variation to work with.

In many previous studies of technological diffusion, the presumption has been that firms do not adopt because they do not know about a technology. This is the assumption underlying "epidemic" models of diffusion, one of the two main categories of diffusion models reviewed by Geroski (2000). While lack of knowledge about the technology may explain the lack of take-up in the cash-drop and no-drop groups,[29] this cannot be the explanation for low adoption among the tech-drop group, because we gave them the technology. We ourselves manipulated the firms' information set.

Another natural hypothesis is simply that the technology does not reduce variable costs as much as we have argued that it does. It is possible that there are unobserved problems with the die that we were not aware of. Beyond our arguments about the mathematical superiority of our cutting design and our cost-benefit breakdown, a key piece of evidence against this hypothesis is the revealed preference of the six firms who adopted. In particular, the one adopter in the no-drop group, which we refer to as Firm Z, is one of the largest firms in Sialkot. This firm ordered 32 offset dies on 9 separate purchasing occasions between May 2012 and August 2013, and has ordered more dies since then. Figure 15 plots the timing and quantity of its die orders. In March-April 2013 (round 4 of our survey) the firm reported that it was using the offset die for approximately 50 percent of its production, and has since reported that the share has risen to 100 percent. The firm had abundant time to evaluate the efficacy of the offset die and subsequently placed multiple additional orders. It would be hard to rationalize this behavior if the offset die were not profitable for this firm.

A third hypothesis is that the fixed costs are larger than we have portrayed them to be. In this scenario, fewer firms would find it profitable to adopt and the firms for which it would be worth paying the fixed cost would be those that produce at a sufficient scale or who specialize in higher quality balls. (Firms that produce higher quality balls use higher-quality imported rexine and so may have stronger incentives to adopt since rexine accounts for a larger portion of their unit costs.) To examine these hypotheses, Table 8 estimates a linear probability model relating adoption to firm characteristics pertaining to scale and quality. Given the low levels of adoption, we are unable to infer correlates of adoption with precision. That said, we find little evidence that either scale or quality matters for the adoption decision. There is a marginally significant relationship between output and adoption for non-tech-drop firms, but this is due entirely to

[29] We have collected information on knowledge flows between firms, and Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen (2014) investigates them in more detail.

the fact that the one non-tech drop adopter is a large firm. Within the tech-drop group, there is no significant relationship between scale and adoption. Nor is the share of balls that use the standard "buckyball" design (captured by the "share standard (of size 5)" variable) significantly associated with adoption. The one quality-related variable that has a marginally significant relationship with adoption, the price of size 5 training balls, has a negative coefficient, opposite to what one would expect based on the hypothesis above. The only variable that appears to be significantly associated with adoption is assignment to the tech-drop treatment in the first place.

A fourth hypothesis is that firms differ in managerial talent, and that only talented managers either identify the gains from the new technology or are able to implement the new technology in an efficient way. A fifth, related hypothesis is that adoption depends on worker skill, especially of the cutter. Table 9 reports results of linear models with several measures of manager and worker characteristics as covariates. There is no significant relationship between manager education or experience, age of the firm, head cutter experience, tenure, or score on a Raven's IQ-type test. There is also no significant relationship with whether cutters are paid piece rate or the level of piece rate. The one variable that appears marginally significant is the number of pentagons per sheet achieved with the traditional die (rescaled as in Table 1 discussed above), which can be interpreted as a direct measure of the skill of the cutter. But this variable is not robust to the simultaneous inclusion of other firm characteristics in Column 11.

Given the small number of adopters as of August 2013, it is perhaps not surprising that we have not found robust correlations with firm characteristics. But we do interpret the results of this sub-section as deepening the mystery of why so few firms adopted the new die.

6 Organizational Barriers to Adoption: Motivation and Model

6.1 Qualitative evidence

Puzzled by the lack of adoption, in the March-April 2013 survey round we added a question asking tech-drop group firms to rank the reasons for why they had not adopted the new technology, providing nine options (including an "other" category).[30] Table 10 reports the responses for the 18 tech-drop firms that responded. Ten of the 18 firms reported that their primary reason for not adopting was that their "cutters are unwilling to work with the offset die." Four of the 18

[30]The question asked respondents to "select the main reason(s) why you are not currently using an offset die. If more than one, please rank those that apply in order." The 9 categories were: (1) I have not had any orders to try out the offset die. (2) I have been too busy to implement a new technology. (3) I do not think the offset die will be profitable to use. (4) I am waiting for other firms to adopt first to prove the potential of the technology. (5) I am waiting for other firms to adopt first to iron out any issues with the new technology. (6) The cutters are unwilling to work with the offset die. (7) I have had problems adapting the printing process to match the offset patterns. (8) There are problems adapting other parts of the production process (excluding printing or cutting problems) (9) Other [fill in reason].

said that their primary problem related to "problems adapting the printing process to match the offset patterns" and five more firms selected this as the second-most important barrier to adoption. This issue may be related to the technical problem of re-designing printing screens, but as noted above the cost of a new screen from an outside designer is approximately US$6. It seems likely that the printing problems were related to resistance from the printers. (The other popular response to the question, to which most firms gave lower priority, was that the firm had received insufficient orders, consistent with the scale hypothesis above.)

The responses to the survey question were consistent with anecdotal reports from several firms. One notable piece of evidence is from the firm we have called Firm Z, the large adopter from the no-drop group. As noted above, more than 90 percent of firms in Sialkot pay piece rates to their cutters. Firm Z is an exception: in part because of pressure from an international client, for several years the firm has instead paid a guaranteed monthly salary supplemented by a performance bonus, to guarantee that all workers earn at least the legal minimum wage in Pakistan. While we do not find a statistically significant relationship on average between whether a firm pays a piece rate and adoption (see Table 9), we view the fact that this large early adopter uses an uncommon pay scheme as suggestive.

We also feel that it is useful to quote at some length from reports to us from our own survey team.[31] To be clear, the following reports are from factory visits during the second experiment, which is described in Section 7 below, and we are distorting the chronology of events by reporting them here. But we feel that they are useful to capture the flavor of the owner-cutter interactions that we seek to capture in the theoretical model. As mentioned above and described in more detail below, in our second experiment we offered one cutter in each firm (conditional on the approval of the owner) a lump-sum US$150 (15,000 Rupees, denoted PKR) incentive payment to demonstrate competence in using the offset die.[32] The following excerpts are all from firms in the group assigned to treatment for the second experiment (Group A).

In one firm, the owner told the survey team that he was willing to participate in the experiment but that the team should ask the cutter whether he wanted to participate. The report continues:

> *[The cutter] explained that the owner will not compensate him for the extra panels he will get out of each sheet. He said that the incentive offer of PKR 15,000 is not worth all the tensions in future.*

It appears in this case that the cutter is seeking to withhold information about the new die in order to avoid a future decline in the effective wage. The firm was not treated.

[31] The team included our research assistant, Tariq Raza, who wrote the reports, and the staff of the RCONS: Research Consultants survey firm.

[32] We also offered one printer per firm an incentive payment of US$120, as described below.

In another firm, the owner, who had agreed to participate in the treatment, was skeptical when the enumerators returned to test the competence of the cutter with the new technology. Our survey team writes,

> *[The owner] told us that the firm is getting only 2 to 4 extra pentagon panels by using our offset panel... The owner thinks that the cost savings are not large enough to adopt the offset die... He allowed us to time the cutter.*

The team then continued to the cutting room without the owner.

> *On entering the cutting area, we saw the cutter practicing with our offset die... We tested the cutter... He got 279 pentagon pieces in 2 minutes 32 seconds... The cutter privately told us that he can get 10 to 12 pieces extra by using our offset die.*

The owner then arrived in the cutting area.

> *We informed the owner about the cutter's performance. The owner asked the cutter how many more pieces he can get by using the offset die. The cutter replied, "only 2 to 4 extra panels."*

It appears that the cutter had been misinforming the owner. But the cutter was not willing to risk dissembling in the cutting process itself.

> *The owner asked the cutter to cut a sheet in front of him. The cutter got 275 pieces in 2 minutes 25 seconds. The owner looked satisfied by the cutter's speed... The owner requested us to experiment with volleyball dies.*

This firm subsequently adopted the offset die.

In a third firm, the owner reported that he had modified the wage he pays to his cutter to make up for the slower speed of the new die. Our team writes,

> *[The owner] said that it takes 1 hour for his cutter to cut 25 sheets with the conventional die. With the offset die it takes his cutter 15 mins more to cut 25 sheets for which he pays him pkr 100 extra for the day which is not a big deal.*

This firm has generally not been cooperative in our survey, and we have not been able to verify that the firm has produced more than 1,000 balls with the offset die, and for this reason is not classified as an adopter. But we suspect that it will be revealed to be an adopter by our definition in a future survey round.[33]

[33] Our survey team's report continues,

> *He told us that his business is worth pkr 40 million. By giving him just pkr 4000 worth of die, we are trying to get a lot of information out of him which he doesn't like to give. He said that we are lucky because our offset die really works (give[s] better results); that's why he got trapped. Else he wouldn't have responded to us at all.*

6.2 A model of organizational barriers to adoption

The survey results and anecdotes point to misaligned incentives within the firm an explanation for limited technology adoption. If firms pay piece rates and do not modify the payment scheme when adopting, owners enjoy the gains from reduced input costs, but cutters — and to a lesser extent printers — bear the costs of increased labor time. While the reduction in input costs are an order of magnitude greater than the increase in labor costs, workers' incomes may nonetheless decline substantially, certainly during the initial phase of learning to use the new die and possibly in the longer run. If the payment scheme remains unchanged, workers have an incentive to misinform the owner about the value of the technology. The interesting question is why owners are influenced by the misinformation from workers, given that they are presumably aware that workers have such an incentive.

We now develop a cheap-talk model in a principal-agent setting that captures these intra-firm dynamics and motivates our second experiment. The model is designed to be as simple as possible but still to capture what we believe are the main forces at play. Specifically, it shows that under certain parameter values there exists a scenario in which a perfectly informed cutter, acting rationally, misinforms an imperfectly informed owner about the value of a beneficial technology and the owner, also acting rationally, does not adopt. We then describe an organizational innovation, a small expansion of the contract space, that can alleviate the misaligned-incentives problem and that maps closely into the incentive-payment experiment described below.

As discussed in the introduction, our model combines insights from the literatures on strategic communication (e.g. Crawford and Sobel (1982)) and contracting within the firm (e.g. Gibbons (1987) and Holmstrom and Milgrom (1991)). We view the model primarily as an application of ideas from these literatures to our setting.

6.2.1 Set-up

Consider a one-period game. There is a principal (she) and an agent (he). The principal can sell output at a price p. The principal incurs two costs: a constant marginal cost of materials $C(q) = cq$ and a wage $w(q)$ that she pays to the agent. The principal's payoff is therefore given by $pq - w(q) - cq$. The agent produces output $q = sa$ where s is the productivity of the technology (e.g. the cuts per minute or speed), and a is effort, which is not contractible. The agent expends effort at a cost of $e(a) = \frac{a^2}{2}$ and has utility $U = w(q) - \frac{a^2}{2}$.

There is a new technology. Adopting the new technology requires a fixed cost, F. The new technology potentially affects the agent's speed, s, and the materials cost, c. The old technology has known parameters (s_0, c_0). The new technology can be one of three possible types:

1. Type 1 has parameters (c_1, s_1), with $c_1 = c_0$ and $s_1 < s_0$. This technology is dominated by the existing technology because it does not lower material costs and is slower. We refer

to this as the “bad” technology.

2. Type 2 has parameters (c_2, s_2), with $c_2 < c_0$ and $s_2 < s_0$. This technology lowers material costs but is slower than the existing technology. This technology is analogous to our new die.

3. Type 3 has parameters (c_3, s_3), with $c_3 = c_0$ and $s_3 > s_0$. This technology dominates the existing technology because it has the same material costs but is faster.

The principal has prior ρ_i that the technology is type i, with $\sum_1^3 \rho_i = 1$. We assume that the agent knows the type of technology with certainty. We believe that this assumption is reasonable since, as shown through the anecdotes, the cutters seem to be more knowledgeable about the efficacy of a cutting technology than owners with less specialized expertise.

We assume that contracts must be of the linear form $w(q) = \alpha + \beta q$, where $\beta > 0$. We further assume that the agent has limited liability, $\alpha \geq 0$ — a reasonable assumption given that no worker in our setting pays an owner to work in the factory. Below we will consider cases which differ in the ability of the principal to condition the piece rate, β, on marginal cost, c, a characteristic of the technology that will in general only be revealed ex post.

The timing of the game is as follows. In Stage 1, the principal chooses a wage contract.[34] In Stage 2, Nature reveals the technology type to the agent. In Stage 3, the agent can send one of three costless messages, $\{m_1, m_2, m_3\}$, regarding the type of the new technology. In Stage 4, the principal decides whether or not to adopt the new technology, given the agent's message. In Stage 5 the profits and payments are realized and the technology is revealed to the principal. The key feature of the timing is that the wage contract must be chosen before the characteristics of the technology are signaled by the agent.[35]

6.2.2 Benchmark cases

As preliminary steps, it is useful to solve the model in two benchmark cases, one in which the principal is fully informed about the technology and one in which the principal is imperfectly informed and receives no signal from the agent.

Benchmark 1: Fully informed principal

In this case, the fully informed principal optimizes profits subject to the agent's participation

[34] We restrict attention to a single contract rather than a menu of contracts since there was no evidence such menus were on offer in Sialkot.

[35] Since Nature does not reveal the technology type to the principal, it is not crucial for the analysis whether Nature's move, which we can think of as the initial technology drop by our survey team, happens before or after the wage contract is set. (That is, the order of Stages 1 and 2 can be reversed.) Thus the model can also accommodate a scenario in which the principal's priors are set when our survey team does the technology drop and the technology type is revealed to the agent.

constraint (PC); the incentive compatibility constraint (ICC), i.e. that the agent chooses effort optimally; and the limited liability constraint (LLC), $\alpha \geq 0$. Conditional on having adopted a technology of type i, the principal's problem is:

$$
\begin{aligned}
\max_{a,\beta} \quad & p s_i a - (\alpha + \beta s_i a) - c_i s_i a & & \text{s.t.} \\
& \alpha + \beta s_i a - \tfrac{a^2}{2} & \geq 0 \quad & \text{(PC)} \\
& \arg\max_a \alpha + \beta s_i a - \tfrac{a^2}{2} & = a \quad & \text{(ICC)} \\
& \alpha & \geq 0 \quad & \text{(LLC)}
\end{aligned}
$$

where we have assumed that the agent's outside option is zero. The optimal effort choice for the agent is $a = \beta s_i$. As is well known, in the absence of the limited-liability constraint the principal would make the agent the residual claimant: she would set $\beta = p - c_i$ and bring the agent down to his reservation utility through a negative value of α. With the limited-liability constraint this is not possible. Since the agent's effort is independent of α, the principal will set $\alpha = 0$. Given the agent's effort choice, the optimal contract for the principal, for a known technology i, is:

$$\alpha_i = 0,\ \beta_i = \frac{p - c_i}{2} \tag{1}$$

Note that the optimal piece rate depends on marginal cost. Since $c_1 = c_3 = c_0$, the optimal piece rate for technologies 1 and 3 is the same as under the existing technology. The optimal piece rate for the material-saving technology, technology 2, is higher since $c_2 < c_0$. In this case, the principal wants to incentivize more effort from the agent because profits per cut are higher.

It will be convenient below to write the principal's profit from adopting technology i, given the agent's effort choice, as a function of piece rate β (which need not be optimal):

$$\pi_i(\beta) \quad = \quad s_i^2 \beta \left(p - \beta - c_i\right) - F \cdot \mathbb{1}(i = 1, 2, 3) \tag{2}$$

Benchmark 2: Imperfectly informed principal, no signaling from agent

In this case, the imperfectly informed principal must base her decision solely on her priors about the technology type. Following the same logic as above, it can be shown that the principal chooses the wage contract:

$$\alpha = 0, \widetilde{\beta} = \sum_{i=1}^{3} \lambda_i \beta_i \tag{3}$$

where β_i is as in (1) and $\lambda_i = \frac{\rho_i s_i^2}{\sum_1^3 \rho_i s_i^2}$. The optimal piece rate is a weighted average of the optimal piece rates in the full-information case. Given this contract, the expected profit from adoption is:

$$\widetilde{\pi}(\widetilde{\beta}) = \left(\sum_{i=1}^{3} \rho_i s_i^2\right)\left(\widetilde{\beta}\right)^2 - F \tag{4}$$

6.2.3 Imperfectly informed principal, with signaling from agent

We now turn to the setting of primary interest in which the principal is imperfectly informed and can receive messages from the agent about the type of the new technology. We consider two cases, one in which the principal cannot condition the wage payment on marginal cost, which is only revealed ex post, and one in which she can, subject to a fixed transaction cost.

As noted above, the aim of the model is to capture the intra-organizational dynamics we have observed, in particular that workers may misinform owners about the value of the technology, discouraging adoption, and that a simple modification of wage contracts can lead to successful adoption. These features are not present under all possible parameter values. In order to focus attention on what we consider to be the interesting case in the model, we impose three parameter restrictions. Using the definitions of β_i from (1), of $\pi(\cdot)$ from (2), and of $\widetilde{\pi}(\widetilde{\beta})$ from (4), the restrictions can be stated as follows:

$$\pi_2(\beta_0) > \pi_0(\beta_0) \tag{5a}$$

$$\pi_3(\beta_2) > \pi_0(\beta_2) \tag{5b}$$

$$\pi_0(\beta_0) > \widetilde{\pi}(\widetilde{\beta}) \tag{5c}$$

The motivation for these conditions will be clearer below, but let us explain briefly here. Condition (5a) requires that type 2 be more profitable for the firm than the existing technology even under the optimal piece rate for the existing technology (which is not optimal for type 2). This in turn implies $\pi_2(\beta_2) > \pi_0(\beta_0)$, i.e. a fully informed principal would adopt type 2. Condition (5b) implies that technology 3 dominates the existing technology even at the optimal piece rate for technology 2. This in turn implies $\pi_3(\beta_3) > \pi_0(\beta_0)$, i.e. a fully informed principal would adopt type 3.[36] Condition (5c) requires that a principal with no information beyond her priors would choose not to adopt.

No conditional contracts

First we consider the case in which the principal in Stage 1 is unable to condition the wage contract on marginal cost. In this case, there is an equilibrium in which, if the technology is type 2, the agent misinforms the principal about it and the principal does not adopt.

[36] From (2), the derivative of $\pi_3(\beta) - \pi_0(\beta)$ is weakly negative over the range $\beta \in [\beta_0, \beta_2]$.

Proposition 1. *In the game described above (without conditional contracts), the following set of strategies is part of a perfect Bayesian equilibrium.*

1. *Agent's strategy:*

   (a) *If the technology is type 1 or type 2, signal* m_1

   (b) *If the technology is type 3, signal* m_3*.*

2. *Principal's strategy:*

   (a) *Offer wage contract* $\left(\alpha^* = 0, \beta^* = \frac{p-c_0}{2}\right)$

   (b) *If agent signals* m_2 *or* m_3*, adopt.*

   (c) *If agent signals* m_1*, do not adopt.*

The formal proof is in appendix A.2. In this case the principal must commit in Stage 1 to a particular piece rate not conditioned on cost. Given that she has done so, the agent strictly prefers the existing technology to type 2. So if the technology is type 2, the agent signals that it is type 1, the bad technology, to discourage adoption. Why does the principal pay attention to the agent's signal, given that she knows that the agent has the incentive to misinform her in this way? The general answer is the agent's signal may be "influential" in the sense discussed by Sobel (2013) when two conditions are satisfied: (1) the agent's and principal's interests are sufficiently aligned that for some technology types the agent and principal favor the same adoption decision, and (2) the agent's preferences over adoption vary across technology types. These conditions are satisfied here: the players' interests are aligned if the technology is of type 1 or 3, and the agent's preferences for adoption differ across these types. The agent's advice is valuable enough in these states of the world that it is worthwhile for the principal to follow the agent's advice and allow herself to be misled in the type-2 state rather than to ignore the agent's advice altogether.

There is also a "babbling" equilibrium in which the principal ignores what the agent says and the agent can say anything he pleases. In this equilibrium, the principal bases her decision solely on her priors, as in Benchmark 2 above. Given condition (5c), she does not adopt. As in other cheap-talk models, there are many other possible equilibria. The literature has developed a number of equilibrium refinements to eliminate implausible equilibria, which are not our focus here; see Sobel (2013) for further discussion.

An important question that arises here is whether there exists an equilibrium in which the agent reveals the technology type truthfully. It turns out that under conditions (5a)-(5c) there does not.

Proposition 2. *In the game described above, there is no perfect Bayesian equilibrium under which the agent always truthfully reveals the technology type.*

The formal proof is in Appendix A.3. Intuitively, if the agent were to reveal the technology type truthfully, then under our conditions the principal would want to adopt type 2 and not type 1. But given this strategy of the principal, and the fact that the wage contract is fixed ex ante, the agent would be better off misreporting type 2 to be type 1, discouraging adoption.

Conditional contracts

Now suppose that the principal can pay a fixed transaction cost, G, and have access to a larger set of wage contracts, in particular to contracts that condition the piece rate on marginal cost, c. Recall that the optimal contracts under the existing technology and types 1 and 3 are identical (since $c_3 = c_1 = c_0$ and hence $\beta_3 = \beta_1 = \beta_0$). The ability to condition on marginal cost is useful only for technology type 2. Allowing for conditioning, the principal can offer contracts of the form:

$$w(q) = \alpha + (\beta + \gamma)q \qquad \text{if } c = c_2 \tag{6}$$

$$w(q) = \alpha + \beta q \qquad \text{if } c \neq c_2$$

It turns out that if G is sufficiently small, then there will exist an equilibrium in which the agent reveals truthfully.

Proposition 3. *In the game described above (with conditional contracts), if*

$$G < \rho_2 \left[\pi_2(\beta_2) - \pi_0(\beta_0)\right] \tag{7}$$

then the following set of strategies is part of a perfect Bayesian equilibrium.

1. *Agent's strategy:*
   (a) *If the principal pays G, signal truthfully.*
   (b) *If the principal does not pay G:*
      i. *If the technology is of type 1 or 2, signal m_1.*
      ii. *If the technology is of type 3, signal m_3.*
2. *Principal's strategy:*
   (a) *Pay G and offer wage contract* $\left(\alpha^{**} = 0, \beta^{**} = \frac{p-c_0}{2}, \gamma^{**} = \frac{c_0-c_2}{2}\right)$
   (b) *If the agent signals m_1, do not adopt.*
   (c) *If the agent signals m_2 or m_3, adopt.*

The proof is in Appendix A.4. Intuitively, if the principal offers the conditional contract, the higher piece rate if $c = c_2$ is enough to induce the agent to prefer adoption if the technology is of type 2.[37] Paying the fixed cost, G, will be in the interest of the principal if (7) is satisfied, which is to say that the expected additional profit from adopting type 2 (with the optimal piece rate for type 2) is greater than the fixed cost of gaining access to the new contract. In this case, the availability of the conditional contract solves the misinformation problem, in that type 2 will be adopted in equilibrium. At the same time, if the fixed cost G is high (i.e. if (7) is not satisfied), then there again exists the equilibrium of Proposition 1, in which type 2 is not adopted. It is worth emphasizing that condition (7) is a statement about the costs of contract modification relative to the expected additional profit from adopting the type-2 technology, which depends on the principal's prior that the technology is of type 2, ρ_2. If the principal is initially very skeptical, she may not be willing to offer the conditional contract even at a very modest fixed cost.

6.2.4 Discussion

The theory so far carries three main implications. First, under piece-rate contracts that cannot be conditioned on marginal cost, there is an equilibrium in which cutters misinform owners about the value of our technology and owners fail to adopt it. Second, again under non-conditioned contracts, some information that the cutters have about technologies is necessarily lost because of conflicting incentives within firms. Third, if the transaction cost of changing contracts is sufficiently low, an expansion of the contract space to allow piece rates to be conditioned on marginal cost (an ex-post-revealed characteristic of the technology) leads to truthful revelation by the cutter and adoption by the owner.

A natural question that arises in this environment is why, if the simple contract modification can solve the misinformation problem, owners would not simply offer the conditional contracts on their own. Our model suggests two possible reasons, which we believe apply in the real-world context. One reason, corresponding to the no-conditional-contracts case, is simply that the principal is unaware of the existence of the conditional contract. In this sense, the conditional contract may be an organizational innovation that was previously unknown, at least to some firms, in the same way that our offset die and cutting design was previously unknown.

Another reason, corresponding to the conditional-contracts case, is that the principal is aware of the conditional contract, but perceives the cost of implementing the conditional contract to be higher than the expected benefit. The fixed transaction cost of offering the new contract can be interpreted in a number of different ways. It may be that social norms have arisen around standard piece-rate contracts, such that firms incur a cost in terms of reduced worker morale

[37] Note that, using the notation of (1), $\beta^{**} = \beta_0$ and $\beta^{**} + \gamma^{**} = \beta_2$, the optimal piece rate for type 2 in the full-information case.

if they deviate from the contract perceived to be normal or fair. The fixed cost can also be interpreted as a cost of accessing a commitment device to make credible the principal's pledge to raise the piece rate if the technology is type 2. Although the principal may promise to alter the piece rate in this way, such a promise is unlikely to hold up in a court, particularly in a setting with relatively weak legal institutions such as Sialkot, and committing credibly to modifying the piece rate may be quite costly. In our simple model, such commitment would not be needed since the firm would want to pay the higher piece rate ex post, but such a commitment device might be needed in more complicated models.

Finally, the fixed cost can be interpreted in light of the well-known ratchet effect (e.g. Gibbons (1987)). If a worker paid a piece rate discovers a labor-saving innovation, he may not bring these to the attention of the owner if he expects the principal to cut the piece rate in response. As in the Lincoln Electric case discussed in Carmichael and MacLeod (2000), it may be optimal for the principal to commit to not changing the piece rate in order to encourage labor-saving innovations. If most innovations in Sialkot are labor-saving, such concerns may explain why piece rates are sticky and why it may be costly for firms to start offering conditional contracts — contracts that open the door to the ratchet effect. Anecdotally, several firms and die-makers reported to us that the last major cutting innovation was a shift from a one-pentagon die to the two-pentagon non-offset die (e.g. two pentagons sharing a full edge, see Figure 7), which was a labor-saving innovation. It seems plausible that firms in Sialkot expect new cutting technologies to be labor- rather than material-saving and that they are reluctant to modify piece rates for this reason.

These two possible explanations for the stickiness of labor contracts — that owners are not aware of the existence of conditional contracts, and that they do not perceive the benefits of such contracts to outweigh the costs of adopting them — have similar implications for the players' behavior. The misinformation equilibrium exists in both circumstances. The key point is that, for whatever reason, many owners did not in fact adjust labor contracts. This in turn left scope for our incentive intervention, described below, to have an effect.

6.2.5 Theoretical Prediction for Incentive Intervention

Testing our theory empirically presents a number of practical challenges. In principle, one approach would be to pay the transaction cost, G, and examine whether firms change the labor contract and adopt the technology as predicted. But this transaction cost, while well defined in the theory, is not observable and depends on various dimensions of complex social dynamics within firms. It is not clear how much we (as experimenters) would pay, or to whom. Another approach would be to offer the new, conditional piece rate ourselves. That is, we could offer an additional payment per piece to the workers (corresponding to γ in (6)). The practical issue here is that the firms are reluctant to share the detailed production information that would be required to implement such an piece-rate payment. Our challenges in collecting information from firms in the earlier survey rounds indicated to us that it would be impossible to manipulate the piece rate directly in our second experiment.[38]

Facing these constraints, we opted for a third approach: we offered a one-time lump-sum payment to one cutter and one printer per firm, conditional on successful adoption of the new offset die. We discuss the implementation in detail in Section 7 below; here we show conceptually what effect we expect such a conditional incentive payment to have. The key point is that the payment is still expected to solve the misinformation problem in the sense that, if it is sufficiently large, it will induce the cutter to reveal truthfully the efficacy of the new technology.

Formally, suppose that the game is as described in Proposition 3 with two further modifications. First, assume that condition (7) is not satisfied. Second, assume that in Stage 2 a third-party experimenter may offer to modify the labor contract through the addition of an incentive payment and that the principal places a zero prior on this possibility. Then we have the following:

Proposition 4. *In the game described above, suppose that in Stage 2 an experimenter offers an incentive payment L to the agent if the marginal cost is revealed to be c_2. If*

$$L > \frac{(p - c_0)^2(s_0^2 - s_2^2)}{8} \tag{8}$$

then the following set of strategies is part of a perfect Bayesian equilibrium.

1. *Agent's strategy:*
   (a) *If the experimenter offers incentive payment L, signal truthfully.*
   (b) *If the experimenter does not offer incentive payment L:*
      i. *If the technology is of type 1 or 2, signal m_1.*
      ii. *If the technology is of type 3, signal m_3.*
2. *Principal's strategy:*
   (a) *Offer wage contract $\left(\alpha^* = 0, \beta^* = \frac{p-c_0}{2}\right)$*
   (b) *If the agent signals m_1, do not adopt.*
   (c) *If the agent signals m_2 or m_3, adopt.*

[38] In the end, one-third of firms chose not to participate in the much less invasive intervention we decided to implement; see Section 7 below for details. This confirmed our earlier belief that firms' willingness to participate would be limited.

The proof is in Appendix A.5. Intuitively, here the incentive payment, L, plays the same role as the conditional piece rate γ^{**} in Proposition 3: it raises the payoff to the agent of signaling truthfully when the technology is of type 2. The empirical implication is simply that if the lump-sum bonus is sufficiently large it will induce adoption of technology type 2. It is worth noting that "sufficiently large" in this context is relative to the possible wage losses of a single cutter, not to the revenues or profits of a firm. Indeed, we will see below that a lump-sum incentive payment that appears small from the point of view of firms has a large effect on adoption, consistent with this proposition.

7 Experiment 2: The Incentive-Payment Experiment

7.1 Experimental design

Motivated by the hypotheses described in the previous section, we conducted the incentive-payment experiment in September-November 2013. To avoid interfering with the process of diffusion to the non-tech-drop firms from the first experiment, we focused on only the 35 tech-drop firms (including both initial responders and initial non-responders). At the time of randomization, we believed that 34 of these firms were still active. These were divided into the four similarly-sized strata: (1) firms in the two smaller strata from the tech-drop experiment that had not adopted the die as of August 2013, (2) firms in the two larger strata from the tech-drop experiment that had not yet adopted the die, (3) firms from the initial non-responder stratum from the tech-drop experiment that had not yet adopted the die, and (4) firms that had already adopted the die. Within each stratum, firms were randomly assigned in equal proportion to a treatment group (which we call Group A) and a control group (Group B). Three of the 34 assigned firms were subsequently revealed to have stopped manufacturing soccer balls, leaving 15 firms in Group A and 16 in Group B.

To firms in Group B we gave a reminder about the offset die and the new cutting pattern, and informed them about the two-pentagon variant of the offset die (which, as noted above, had proven more popular than the four-pentagon offset die we originally distributed.) We also offered to do a new demonstration with their cutters. To each firm in Group A, we gave the same refresher, the same offer of a new demonstration, and the same information about the two-pentagon variant. In addition, we explained to the owner that cutters and printers paid piece-rates had an incentive to misinform the owner about the value of the technology. We then offered (to the owner) to pay one cutter and one printer lump-sum bonuses roughly equivalent to their monthly incomes — 15,000 Rs (US$150) and 12,000 Rs (US$120), respectively — on the condition that within one month the cutter demonstrate competence in using the new die and the printer demonstrate competence in printing pairs of offset pentagon pieces cut by the new die. If the owner agreed to the intervention, we explained the intervention to one cutter and one printer chosen by the owner, paid them 1/3 of the incentive payment on the spot, and scheduled a time to return to test their performance using the die.[39]

The performance target for cutters was 272 pentagons from a single sheet in three minutes using the new die. The target for the printer was 48 pairs of pentagons cut by the offset die in three minutes.[40] We provided the owner with 20 laminated sheets for his workers to practice with, printing screens for offset pentagon pairs, and a nominal Rs 5,000 ($50) to cover additional costs such as overhead (e.g. electricity while the cutters were practicing). We returned after approximately one month to test the employees and, upon successful achievement of the performance targets, to pay the remaining 2/3 of the incentive payments. Without revealing ahead of time that we would do so, we allowed for a buffer of 30 seconds and 5 pentagons for cutters and 30 seconds for printers.[41]

Table 11 evaluates baseline balance by comparing firm characteristics across Group A and Group B firms at the time of our visit to explain the intervention (September 2013). No differences in means are statistically significant. It appears that randomization was successful.[42]

7.2 Results

Ten of the 15 Group A firms agreed to participate in the experiment.[43] Table 12 reports the times achieved by the chosen cutter at each firm. The average time was 2 minutes and 52 seconds, approximately 27 percent longer than the average time to cut with the traditional die (2 minutes and 15 seconds). The minimum time reported using the offset die was 2 minutes and 28 seconds, or 9.6 percent longer than with the traditional die. It is partly for this reason, and partly because cutters do not need to change sheets as frequently with the new die, that we believe that the 50 percent increase in labor time factored into the cost calculations above in Section 3 is conservative. In addition, many cutters expressed confidence that with additional use they could lower their cutting time. All printers easily achieved their target, consistent with the assumption in Section 3 that, despite some printers' fears, the new die does not increase labor time for printing.

[39]To the extent possible, we attempted to make the payment directly to the cutter and printer. In two cases, the owner insisted that we pay him and that he pass on the money to the employees, and we acceded to this request.

[40]The 3-minute targets were chosen after conducting speed tests at two of the pilot firms mentioned in Section 5. They are approximately one third higher than the time to cut a single sheet using the original die and the time to print 48 two-pentagon panels cut using the original die.

[41]That is, the effective target for cutters was 267 pentagons from one sheet in 3 minutes 30 seconds, and for printers was 48 pairs in 3 minutes 30 seconds.

[42]Because of an error by our enumerators, one firm that was assigned to Group B was offered the incentive-payment intervention. This occurred while two co-authors of the paper were in the field, and the error was caught within hours of its occurrence. To maintain balance, we randomly selected one as-yet-untreated Group A firm from the same stratum and re-assigned it to Group B.

[43]In two of these 10 firms, it was not possible to complete the printer performance test.

In order to investigate adoption in response to the incentive-payment intervention, we carried out a survey round in January-March 2014, 2-5 months after the completion of the intervention.[44] As above, we classify a firm as an adopter if it reports that it is currently using the offset die and has produced more than 1,000 balls with it in the past month. Of the 10 Group A firms that agreed to participate in the experiment, two firms had already adopted the die at the time we ran the incentive experiment. Of the remaining 8 firms, 5 firms subsequently adopted. Of the 16 Group B firms, 3 firms had already adopted prior to the invention. None of the remaining 13 firms subsequently adopted.

Table 13 formally assesses the impact of the incentive-payment intervention on adoption rates. All regressions include dummies for the four strata described above. Columns 1-4 include all strata, and Columns 5-8 omit the stratum of firms that had already adopted by August 2013. The first-stage estimates (Columns 1 and 5) indicate, not surprisingly, that assignment to Group A is significantly associated with greater probability of receiving the incentive-payment treatment; that is, we have a strong first stage. The dependent variable in Columns 2-4 and 6-8 is a 0/1 indicator for whether a firm has adopted, i.e. is currently using the offset die and has produced more than 1,000 balls using it. The OLS estimates in Columns 2 and 6 are positive and significant, but one might be worried about selection into treatment. The reduced-form (intent-to-treat) results in Columns 3 and 7 do not suffer from such selection issues and indicate a positive and significant (at the 5 percent level) causal relationship between assignment to Group A and adoption. Adoption rates increased by 0.32 among the treatment group or by 0.38 if we restrict attention to only the firms who had not already adopted at the start of the experiment. The IV estimates (the effect of treatment on the treated) are substantially higher (0.48 or 0.63 if we restrict attention only to initial non-adopters). However, since the one third of firms who refused the intervention may have chosen to do so because of particularly large costs of adoption (or small benefits), these IV estimates should be treated with caution.

To check robustness, Table 14 reports results using an alternative indicator of adoption, namely whether the firm purchased its first offset die (beyond the trade-in that we paid for) after September 1, 2013. Of the eight firms that accepted the intervention and had not adopted by August 2013, three subsequently purchased their first offset die. (One of these firms had not produced with it yet at the time of our most recent survey.)[45] Table 14 shows that the positive causal effect of the incentive-payment treatment on adoption is robust to using this alternative measure.

It is important to acknowledge that the sample sizes in the incentive-payment experiment are

[44]In one case, the firm's report regarding adoption was ambiguous and our enumerators followed up with the firm to clarify in May 2014.

[45]In addition, one large Group-A firm that was already classified as an adopter because it was using the offset cutting pattern for table cutting (see footnote 12), purchased its first die (beyond the four-panel offset die we originally gave) following the beginning of our intervention.

small. An alternative to large-N statistical inference are permutation tests whose properties are independent of sample size (see Bloom, Eifert, Mahajan, McKenzie, and Roberts (2013) for the use of this type of inference in a similar context). We determine the proportion of all possible treatment assignments that produce coefficients as large as or larger than the ones we find. This procedure produces an exact p-value and does not require any asymptotic approximations. Given the selection discussion above, we focus on the more conservative ITT estimates in columns 3 and 7 of Tables 13 and 14. Within each of the four strata, we assigned treatment status with 50 percent probability. The stratum of smaller firms contained 6 firms, the stratum of larger firms contained 12 firms, the stratum of initial non-responders contained 8 firms and the stratum of already-adopters contained 5 firms. This means there are $25,872,000 = \binom{6}{3}\binom{12}{6}\binom{8}{4}\left(\binom{5}{2} + \binom{5}{3}\right)$ possible treatment assignments.[46]

Figure 16 plots the distribution of coefficients obtained from regressing die use on assignment to group A for the millions of possible treatment assignments. The left panel reports the distribution of outcomes under the specifications with all strata and the right panel reports outcomes from the initial non-adopters sample only. The vertical line in both figures denotes the observed ITT effects reported in columns 3 and 7 of Table 13. Note that there are only a handful of possible coefficients despite the several million possible permutations. This is because of the small number of adopting firms and because no control firm has adopted the die. Yet in both cases, the observed ITT coefficients are the largest effects that could have been observed under any treatment assignment. In other words, there is no possible outcome that is more extreme than the one we observe in each specification. We can use the distribution to construct p-values for the hypothesis test that the coefficients we find are different from zero. For our main measure of adoption, current use, the p-value is 3.04 percent in both the all firm and initial non-adopter samples. Figure 17 presents a similar analysis for our alternative indicator of adoption, die purchases, with corresponding p-values of 4.28 percent in the all-firm sample and 21.42 percent in the initial non-adopters sample.

The results indicate a robust effect of the incentive payment treatment on adoption. Considering current use ($> 1,000$ balls) as the outcome, it is striking that over half of the treated firms that had not previously adopted responded to the treatment. As we discuss in the next section, It seems hard to rationalize such a large response to such a small incentive, unless the incentive is helping to resolve an organizational bottleneck within the firm.

7.3 Examining Alternative Explanations for Increase in Take-up

In this sub-section, we examine two alternative explanations for our finding that a small incentive payment substantially increased adoption.

[46] If we exclude the already-adopter stratum, there are $1,293,600 = \binom{6}{3}\binom{12}{6}\binom{8}{4}$ possible permutations.

7.3.1 Alternative hypothesis: subsidies for fixed costs

The first alternative we consider is that there was no information transmission from workers to owners, but that we mechanically induced firms to adopt by subsidizing the fixed costs of adoption. This explanation is best seen through the lens of the model. In the model, suppose that the owner is aware of conditional wage contracts and that there is no cost of using them, $G = 0$. The owner then simply weighs the variable cost reduction from the new technology against the fixed costs of adoption. These fixed costs may include a lump-sum wage bonus to workers to compensate them for a learning period where they will earn less. Our incentive-payment experiment could be seen as providing a subsidy to cover some of these fixed costs of adoption, and the subsidy may itself have induced the owner to adopt.

Is this a quantitatively plausible explanation of our findings? To organize our thinking about this question, we can write the present discounted value of expected additional profit from adoption for firm f as follows:

$$\Pi_f = -FC_{f0} + Pr(success)_f \sum_{t=1}^{\infty} \frac{NVB_f}{(1+r_f)^t} \tag{9}$$

where FC_{f0} are fixed costs of adoption, which must be paid up front and may be firm-specific; $Pr(success)_f$ is the probability perceived by the firm that the technology works as we said it does; NVB_f are net variable benefits per cutter per month; and r_f is the interest rate faced by the firm. Net Variable Benefits can be calculated for each firm following the method of Section 3.2. For firms that did not have to buy the die, which correspond to the tech-drop firms in the incentive-payment experiment, observed fixed costs are Rs 10,800/US\$108.[47] In this section, we make the assumption that the Rs 32,000/US\$320[48] we paid in the incentive-payment treatment were also necessary and part of the true fixed cost of adoption.[49] We thus take the total observed fixed costs to be Rs 42,800/US\$428.[50] The assumption regarding wage payments seems conservative. In the incentive-payment experiment, only one worker felt that the payment was insufficient to cover his costs of adoption, suggesting that the incentive payments were greater than the "training" cost faced by workers in the great majority of firms.

As a first step toward answering the quantitative plausibility question, suppose that there

[47] Rs 800/US\$8 to have screens redesigned and remade and Rs 10,000/US\$100 for a new die for the hole-punching machine; see Section 3.2 for further details.

[48] Rs 15,000/US\$150 to the cutter, Rs 12,000/US\$120 to the printer, plus Rs 5,000/US\$50 to the owner to cover overhead.

[49] In Section 3.2 we assumed that workers wages went up by 50% to compensate them for using the slower technology. The discussion in Section 6 suggests that many firms do not adjust their wages and so in this section we remove this component and instead assume that the firm must only pay the one-off conditional wage payment.

[50] This calculation uses net variable benefits per cutter since we assume that the fixed costs need to be paid for each cutter in the firm. This is a conservative assumption since it is possible that firms could, for example, share the hole-punching machine across cutters.

is no uncertainty about the technology (i.e. $Pr(success)_f = 1$) and no unobserved fixed costs beyond the US$428 mentioned above. Under these assumptions, (9) can be reconciled with non-adoption only if firms face extremely high interest rates and hence have a small effective discount factor $1/(1 + r_f)$.[51] For initial non-adopters, the values of firm-specific interest rates that set $\Pi_f = 0$ in (9) represent lower bounds on the firm-specific interest rates. At the 10^{th} percentile, the lower bound is 7.8% per month; at the 90^{th} percentile, the lower bound is 70.7% per month. In our baseline survey, we asked firms explicitly about the interest rates they face, and the responses ranged from 3% to 19% per *year*; these are an order of magnitude lower than the implied lower bound for most firms. That is, in the absence of both uncertainty about the technology and unobserved fixed costs, the interest rates (and rate of discounting) that would be required to explain the low initial rates of adoption appear to be implausibly high.

This argument leaves open the possibility that some combination of uncertainty and unobserved fixed costs can account for the low initial rates of adoption we observed. To address this possibility, we take a different approach: we allow for uncertainty and unobserved fixed costs and ask whether these can explain both the low rates of initial adoption *and* the magnitude of the response to our incentive-payment intervention. The unobserved fixed costs may represent attention costs for the owner or psychic costs involved in changing established routines. We assume, conservatively, that the interest rate is the highest of the self-reported interest rates, 19% per year. As a benchmark, we assume that owners place a 50% probability on the event that the technology works as we described (i.e. $Pr(success)_f = .5$); we consider alternative priors below. Under these assumptions, we can place bounds on the values of unobserved fixed costs that can explain the behavior we observe.[52] These bounds on fixed costs are plotted by rank in Figure 18 for the 31 firms in the incentive-payment experiment. The black outlines represent the lower bounds that would be implied by non-adoption, and the red outlines the upper bounds that would be implied by adoption in response to the incentive-payment intervention.[53]

There are two important points to notice in Figure 18. The first is that, for almost all firms, the US$320 subsidy is small relative to the implied lower bound on fixed costs. At the 10^{th} percentile, the implied lower bound on fixed costs is US$2,286; at the 90^{th} percentile, it is US$20,718. For the vast majority of firms the implied fixed costs are an order of magnitude greater than the subsidy. The second point to note is that the firms' lower bounds are not bunched closely together. Therefore, if a substantial portion of the unobserved fixed costs is

[51]This is another way of stating the argument from Section 3.2.3 that the observable fixed costs of adoption can be recouped within a relatively short amount of time by almost all firms.

[52]In particular, simplifying (9), if a firm does not adopt initially, it must be that $\Pi_f < 0$ and hence that $FC_{f0} > (.5)\frac{NVB_f}{.0146}$. If a firm adopts in response to the incentive-payment experiment, it must be that $\Pi_f > 0$ after the US$320 reduction in fixed costs, and hence that $FC_{f0} < (.5)\frac{NVB_f}{.0146} + 320$.

[53]Firms that initially adopted are indicated by the sold black bars; for these firms, we can conclude only that fixed costs are less than what is indicated by the black outline. The firms that adopted in experiment 2 are indicated by solid green bars.

common across firms, a subsidy of US$320 would only lead to a few firms adopting and hence ITT coefficients much smaller than the ones we found.

We can make these claims more precise by imposing some structure on the distribution of unobserved fixed costs. Suppose that fixed costs are distributed log normally:

$$\ln(FC_{0f}) = \theta + \varepsilon_f \tag{10}$$

where $\varepsilon_f \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. We can use information on adoption in both experiments 1 and 2 to estimate θ and the error variance, σ_ε^2.[54] Panel A of Table 15 reports these estimates $\hat{\theta}$ and $\hat{\sigma}_\varepsilon^2$ under six priors ranging from $Pr(success)_f = .01$ to $Pr(success)_f = 1$.

With these estimates in hand, we can ask: what is the probability that we would observe an effect of a US$320 subsidy on adoption as large as the effect we observed in experiment 2? To answer this question we use $\hat{\theta}$ and $\hat{\sigma}_\varepsilon^2$ to simulate 1,000 fixed cost draws, with Figure 19 displaying the full distribution of Group A firms switching from non-adoption to adoption as a result of a US$320 payment. Panel B of Table 15 reports the corresponding probabilities of 5 or more Group A firms switching. The probability of observing an increase in adoption of that magnitude is exceedingly low, between .000 and .003, for all but the most pessimistic prior of $Pr(success)_f = .01$. Although such a low prior is theoretically possible, it seems unrealistically pessimistic given the nature of the technology.

In Panel C of Table 15, we turn to the corresponding ITT estimates from these simulations. The ITT estimates range between .01 and .08 for priors between $Pr(success)_f = 1$ and $Pr(success)_f = .05$, much lower than the 0.32 we obtained in our incentive-payment experiment. Even for the most pessimistic prior of $Pr(success)_f = .01$, we only obtain an ITT of 0.22. In summary, a US$320 subsidy cannot plausibly explain the magnitude of the increase in adoption we observed in our second experiment. Even when we choose the mean and variance

[54] We estimate the parameters using maximum likelihood. Let $adopt_{1f}$ denote an indicator if firm f had adopted the technology in experiment 1, and $adopt_{2,f}$ an analogous indicator for adoption after experiment 2. The log likelihood function for group A firms is:

$$\begin{aligned} l(\theta, \sigma_\varepsilon) \quad = \quad & \sum_f \Bigg\{ (1 - adopt_{1f})(adopt_{2f}) \ln \left[\Phi\left(\frac{\ln(NVB_f + 320) - \theta}{\sigma_\varepsilon}\right) - \Phi\left(\frac{\ln(NVB_f) - \theta}{\sigma_\varepsilon}\right) \right] \\ & + (1 - adopt_{1f})(1 - adopt_{2f}) \ln \left[1 - \Phi\left(\frac{\ln(NVB_f + 320) - \theta}{\sigma_\varepsilon}\right) \right] \\ & + (adopt_{1f}) \ln \left[\Phi\left(\frac{\ln(NVB_f) - \theta}{\sigma_\varepsilon}\right) \right] \Bigg\} \end{aligned} \tag{11}$$

The first expression on the right-hand-side of (11) captures the contribution to the likelihood of initial non-adopter group-A firms who are induced to switch from non-adoption to adoption because of the $320 subsidy. The second expression captures initial non-adopter group-A firms who are not induced to switch adoption status. The third expression is the contribution of initial adopter firms. We jointly maximize the likelihood function with the group B firms who have the same likelihood function except $adopt_{2f} = 0 \ \forall f$ and there is no US$320 payment inside the argument of the normal CDF, $\Phi(.)$.

of the unobserved fixed costs to best fit the adoption patterns in experiments 1 and 2, a US$320 subsidy can only generate our experimental findings under extremely pessimistic priors.

7.3.2 Alternative hypothesis: salience

A second alternative explanation is that the incentive-payment treatment increased the salience of the new technology and this itself led firms to adopt, independent of any effects on information flows within the firm. There are two variants of this explanation. One variant is that the reminder about the technology during the incentive-intervention visit itself "nudged" firms into adoption. This variant can be quickly dismissed. We gave the same reminder to the control firms for the incentive intervention (Group B firms) and we saw no firms adopt subsequently as a result. Also, it is worth noting that we visited all of the tech-drop firms multiple times as part of our survey rounds. During each of these visits, we discussed the new technology with them and if they were not using it we asked why.

A different variant of the salience story is that by putting more money on the table we sent a stronger signal about our own beliefs about the efficacy of our technology, and this in turn led firms to update their priors about the technology, inducing some firms to adopt. While it is difficult to dismiss this explanation definitively, it also seems unlikely. We believe that it was clear to firms from the outset, in the initial technology-drop implementation, that we believed that the technology was effective. We said so in the initial treatment, and we then demonstrated the efficacy of the technology using firms' own cutters. We then returned to each firm numerous times and, as noted above, in the case of the tech-drop firms we discussed the offset die each time. The amount of money we spent on surveying each firm far exceeded the US$320 payment in the incentive intervention. In short, while in retrospect it seems clear that many owners did not believe us when we told them that the technology works, it does not appear that their skepticism was based on their beliefs about how strongly we held our beliefs, or that the US$320 affected their beliefs about how strongly we held our beliefs. It seems more likely that they believed that we simply had insufficient knowledge and experience in the industry, and hence that our (strongly held) confidence in the technology was misplaced.

8 Conclusion

This paper has two basic empirical findings. First, despite the evident advantages of the technology we invented, a surprisingly small number of firms have adopted it, even among the set of firms that we gave it to. This is consistent with a long tradition of research on technology adoption that has found diffusion to be slow for some technologies, but given the characteristics of our technology — low fixed costs, minimal required changes to other aspects of the production process, limited uncertainty about the cost advantage of the technology — the low adoption rate seems particularly puzzling. Second, with a very small change in the incentives facing key employees in the firm — tiny in monetary terms relative to firms' revenues and the benefits of adoption — we induced a statistically significant increase in adoption. This is consistent with the hypothesis that a misalignment of incentives within the firm — in particular, employees paid piece rate have an incentive to resist adoption of a material-saving technology that slows them down — is an important barrier to adoption. Although for most firms we do not observe directly the communication between employees and owners, it appears that at least one way that employees have resisted the adoption of our new technology is by misinforming owners about the value of the technology. It further appears that the incentive-payment intervention had a significant effect because it induced workers to report truthfully to owners.

The natural question is why many owners did not simply change the payment scheme on their own. We have considered two possible explanations. One is that they were not aware of the availability of alternative payment schemes, or did not understand that an alternative scheme would be desirable. A second possibility is that there are transaction costs involved in changing contracts, even implicit ones. Above we discussed a number of possible reasons for the existence of such costs. Whatever their source, owners may weigh any costs of modifying contracts against the expected benefits of adopting new technologies. If owners have low priors that a beneficial new technology will arrive (or that a technology that has arrived is beneficial), they may rationally be unwilling to pay even quite small transaction costs. These two explanations for the stickiness of wage contracts have similar observable implications, and it is difficult for us to distinguish between them in our context. At the same time, the key point for our study is that many firms did not in fact change their payment schemes, and this left scope for our very modest intervention to have a large effect on adoption.

Although our empirical results are clearly specific to the setting we study, our findings suggest three implications that we believe are likely to apply more broadly. First, we have provided reasonably direct evidence evidence of a complementarity, in the sense of Milgrom and Roberts (1990, 1995), between a technological innovation (the new die) and an organizational innovation (conditional wage contracts). We suspect that similar complementarities between technical and organizational innovations exist in many other settings. This in turn suggests that the study of adoption of particular technologies cannot be divorced from the study of organizational change in the firms doing the adopting.

Second, there appears to be a form of inertia in employment relationships that can hinder technological change. We have argued that firms' choices of labor contracts depend on the rate at which beneficial new technologies are expected to arrive. It also appears that labor contracts, once established, may be difficult to modify. The implication is that industries that evolve in technologically stable environments may be less able to adapt to technological change than new industries. Simple piece-rate contracts may well have been optimal in Sialkot before we showed up, but the very fact that firms in Sialkot have been producing for decades using piece-rates and the same basic production process may itself have contributed to low adoption rates of the new die.

Finally, it seems likely that in order for technology adoption to be successful employees have to have an expectation that they will share in the gains from adoption. Such an expectation may be generated by a variety of different types of contracts, implicit or explicit. But to the extent that owners and managers must rely on the knowledge of shopfloor workers about the value of new technologies or how best to implement them, it appears to be important that a credible gain-sharing mechanism be in place.

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A Theory appendix

A.1 Preliminaries

As a preliminary step, we first establish several properties of the profit functions defined in (2).

Lemma 1. *Given the definition of $\pi(\cdot)$ in (2) and condition (5a), we have:*

$$\pi_2(\beta)-\pi_0(\beta)\begin{cases}<0 & \text{if } 0<\beta<\hat{\beta}_2\\ =0 & \text{if } \beta=\hat{\beta}_2\\ >0 & \text{if } \beta>\hat{\beta}_2\end{cases}$$

where $\hat{\beta}_2=\Omega+\sqrt{\Omega^2+\frac{F}{{s_0}^2-{s_2}^2}}$, $\Omega=\frac{s_0^2\beta_0-s_2^2\beta_2}{s_0^2-s_2^2}$, $\hat{\beta}_2>\Omega$, *and* $0<\hat{\beta}_2<\beta_0$.

Proof. From (2), we can write:

$$\pi_2(\beta)-\pi_0(\beta)=\left({s_0}^2-{s_2}^2\right)(\beta-\Omega)^2+\Omega^2\left({s_0}^2-{s_2}^2\right)-F \tag{A1}$$

This defines a convex parabola with vertex at $\left(\Omega,-\Omega^2\left({s_0}^2-{s_2}^2\right)-F\right)$. Note that $\Omega<\beta_0$ and may be negative. Setting $\pi_2(\beta)-\pi_0(\beta)=0$ define the values of $\hat{\beta}_2$. There is also a negative root, which we can ignore since we are requiring $\beta>0$. The fact that $\hat{\beta}_2>\Omega$ follows immediately from the expression for $\hat{\beta}_2$. The fact that $\hat{\beta}_2<\beta_0$ follows from condition (5a). $\square$

Lemma 2. *Given the definition of $\pi(\cdot)$ in (2) and condition (5b), we have:*

$$\pi_3(\beta)-\pi_0(\beta)\begin{cases}<0 & \text{if } \beta<\hat{\beta}_3\\ =0 & \text{if } \beta=\hat{\beta}_3\\ >0 & \text{if } \hat{\beta}_3<\beta<\hat{\hat{\beta}}_3\\ =0 & \text{if } \beta=\hat{\hat{\beta}}_3\\ <0 & \text{if } \beta>\hat{\hat{\beta}}_3\end{cases}$$

where $\hat{\beta}_3=\beta_0-\sqrt{\beta_0^2-\frac{F}{{s_3}^2-{s_0}^2}}$, $\hat{\hat{\beta}}_3=\beta_0+\sqrt{\beta_0-\frac{F}{{s_3}^2-{s_0}^2}}$ *and* $0<\hat{\beta}_3<\beta_0<\beta_2<\hat{\hat{\beta}}_3<2\beta_0$.

Proof. From (2), we can write:

$$\pi_3(\beta)-\pi_0(\beta)=-\left({s_3}^2-{s_0}^2\right)(\beta-\beta_0)^2+\beta_0^2\left({s_3}^2-{s_0}^2\right)-F \tag{A2}$$

This defines a concave parabola with vertex at $\left(\beta_0,\beta_0^2\left({s_3}^2-{s_0}^2\right)-F\right)$. Condition (5b) implies that $\pi_3(\beta_0)>\pi_0(\beta_0)$, since $\pi_3(\beta)-\pi_0(\beta)$ is decreasing over $(\beta_0,\beta_2]$, and this in turn implies $\beta_0^2\left({s_3}^2-{s_0}^2\right)-F>0$. Setting $\pi_3(\beta)-\pi_0(\beta)=0$ defines the values of the roots, $\hat{\beta}_3$ and $\hat{\hat{\beta}}_3$. The facts that $0<\hat{\beta}_3<\beta_0<\hat{\hat{\beta}}_3<2\beta_0$ follow directly from the expressions for $\hat{\beta}_3$ and $\hat{\hat{\beta}}_3$. The fact that $\beta_2<\hat{\hat{\beta}}_3$ follows from condition (5b). $\square$

Lemma 3. *Given the definition of* $\pi(\cdot)$ *in (2), we have:*

$$\pi_1(\beta) - \pi_0(\beta) \begin{cases} < 0 & \text{if } 0 < \beta < \hat{\hat{\beta}}_1 \\ = 0 & \text{if } \beta = \hat{\hat{\beta}}_1 \\ > 0 & \text{if } \beta > \hat{\hat{\beta}}_1 \end{cases}$$

where $\hat{\hat{\beta}}_1 = \beta_0 + \sqrt{\beta_0^2 + \frac{F}{{s_0}^2 - {s_1}^2}} > 2\beta_0$.

Proof. From (2), we can write

$$\pi_1(\beta) - \pi_0(\beta) = \left({s_0}^2 - {s_1}^2\right)(\beta - \beta_0)^2 - \left({s_0}^2 - {s_1}^2\right)\beta_0^2 - F \tag{A3}$$

which is a convex parabola with roots $\hat{\beta}_1 = \beta_0 - \sqrt{\beta_0^2 + \frac{F}{{s_0}^2 - {s_1}^2}} < 0$ and $\hat{\hat{\beta}}_1$ defined above. Since we have assumed $\beta > 0$, $\hat{\beta}_1$ will not play a role. □

A.2 Proof of Proposition 1

Let $\mu(t_j|m_i, \beta)$ be the principal's belief that the technology is type j, given the agent's signal m_i and the piece rate β. Recall that the principal's priors are ρ_1, ρ_2 and ρ_3. Since m_2 is never signaled on the equilibrium path, $\mu(t_2|m_2, \beta^*)$ is an off-path belief and we specify it to be 1. The principal's beliefs after Stage 3 are then: $\mu(t_1|m_1, \beta^*) = \frac{\rho_1}{\rho_1+\rho_2}, \mu(t_2|m_1, \beta^*) = \frac{\rho_2}{\rho_1+\rho_2}, \mu(t_2|m_2, \beta^*) = 1, \mu(t_3|m_3, \beta^*) = 1$.

To prove the proposition, it suffices to show that there is no profitable deviation for either principal or agent.

A.2.1 No Incentive For Agent to Deviate

First we show there is no incentive for the agent to deviate from his signaling strategy holding fixed the principal's strategy. Note that conditional on the piece rate being held fixed, the agent strictly prefers faster technologies since his utility is increasing in s:

$$U(\beta, s) = \frac{\beta^2 s^2}{2} \tag{A4}$$

For a given piece rate, β, there are three states of the world to consider:

1. If the technology is of type 1, the agent signals m_1 and the principal does not adopt. The agent has no incentive to deviate and signal m_2 or m_3, which will induce the principal to adopt, since $s_1 < s_0$.

2. If the technology is of type 2, the agent signals m_1. The agent does not have an incentive to deviate and signal m_2 or m_3 as this would induce adoption and $s_2 < s_0$.

3. If the technology is of type 3, the agent signals m_3 and the principal adopts. He has no incentive to deviate and signal m_1, which induces the principal not to adopt, because $s_0 < s_3$. He also has no (strict) incentive to deviate and signal m_2, since this also induces adoption and leads to the same payoff as signaling m_3.

A.2.2 No Incentive For Principal to Deviate

Now we show that there is no incentive for the principal to deviate from her adoption strategy, holding fixed the agent's strategy. First we find the optimal adoption strategies for the principal in Stage 4, given the three possible signals she can receive, for all possible wage contracts offered in Stage 1. Then we find the optimal contract the principal offers in Stage 1, anticipating her own behavior in Stage 4.

Optimal Adoption Strategies in Stage 4

For a given β, there are three possible signals by the agent to consider:

1. If the signal is m_1, then the condition for the principal not to deviate can be written:

$$\pi_0(\beta^*) \geq \frac{\rho_1}{\rho_1 + \rho_2}\pi_1(\beta^*) + \frac{\rho_2}{\rho_1 + \rho_2}\pi_2(\beta^*)$$

where the left-hand side is expected profit from non-adoption and the right-hand side the expected profit from adoption. This can be rewritten:

$$\rho_1[\pi_0(\beta) - \pi_1(\beta)] + \rho_2[\pi_0(\beta) - \pi_2(\beta)] \geq 0 \tag{A5}$$

We first show that (A5) holds for $\beta = \beta_0$. In Benchmark 2 above (Section 6.2.2), we showed that $\widetilde{\beta}$ is the optimal piece rate if the principal bases her decision only on her priors and adopts. This implies:

$$\widetilde{\pi}(\widetilde{\beta}) \geq \rho_1\pi_1(\beta_0) + \rho_2\pi_2(\beta_0) + \rho_3\pi_3(\beta_0)$$

By condition (5c), $\pi_0(\beta_0) > \widetilde{\pi}(\widetilde{\beta})$. Hence:

$$\begin{aligned}
\pi_0(\beta_0) &> \rho_1\pi_1(\beta_0) + \rho_2\pi_2(\beta_0) + \rho_3\pi_3(\beta_0) \\
\pi_0(\beta_0) - \rho_3\pi_3(\beta_0) &> \rho_1\pi_1(\beta_0) + \rho_2\pi_2(\beta_0) \\
\pi_0(\beta_0) - \rho_3\pi_0(\beta_0) &> \rho_1\pi_1(\beta_0) + \rho_2\pi_2(\beta_0) \\
(\rho_1 + \rho_2)\pi_0(\beta_0) &> \rho_1\pi_1(\beta_0) + \rho_2\pi_2(\beta_0) \\
\rho_1[\pi_0(\beta_0) - \pi_1(\beta_0)] + \rho_2[\pi_0(\beta_0) - \pi_2(\beta_0)] &> 0
\end{aligned}$$

where the third inequality follows from the fact that $\pi_3(\beta_0) > \pi_0(\beta_0)$ (from condition (5b)). Hence (A5) holds for $\beta = \beta_0$.

Now consider $\beta \in (0, \beta_0)$. By Lemma 3, $\pi_0(\beta) - \pi_1(\beta) > 0$ in this region. For $\beta \in (0, \hat{\beta}_2]$, $\pi_0(\beta) - \pi_2(\beta) \geq 0$ by Lemma 1 and hence (A5) is clearly satisfied. For $\beta \in (\hat{\beta}_2, \beta_0)$, $\pi_0(\beta) - \pi_2(\beta)$ is decreasing in β (refer to (A1), noting that $\Omega < \hat{\beta}_2$); since (A5) is satisfied at β_0, it must be satisfied in this region.

Finally, consider $\beta > \beta_0$. By (A3) and (A1), both $\pi_0(\beta) - \pi_1(\beta)$ and $\pi_0(\beta) - \pi_2(\beta)$ are strictly decreasing in this region. Hence there is a single crossing at which (A5) is satisfied with equality at some $\beta > \beta_0$; call this value $\overline{\beta}$. For $\beta \in (\beta_0, \overline{\beta})$, (A5) holds and the principal has no incentive to deviate and adopt. For $\beta = \overline{\beta}$, (A5) holds with equality and the principal possibly plays a mixed adoption strategy. For $\beta > \overline{\beta}$, (A5) does not hold and the principal has a strict incentive to adopt.

2. If the signal is m_2 then the principal believes that the technology is type 2, given her off-path belief. By Lemma 1, for $\beta < \hat{\beta}_2$, $\pi_2(\beta) < \pi_0(\beta)$ and the principal has an incentive to deviate; for $\beta = \hat{\beta}_2$, $\pi_2(\beta) = \pi_0(\beta)$ and the principal possibly plays a mixed adoption strategy; and for $\beta \geq \hat{\beta}_2$, $\pi_2(\beta) \geq \pi_0(\beta)$ and the principal has no incentive to deviate from adopting.

3. If the signal is m_3, the principal knows that the technology is type 3, i.e. $\mu(t_3|m_3, \beta) = 1$ for any β. By Lemma 2, for $\beta \in (\hat{\beta}_3, \hat{\hat{\beta}}_3)$, $\pi_3(\beta) > \pi_0(\beta)$ and the principal has no incentive to deviate from adoption; for $\beta = \hat{\beta}_3$ or $\beta = \hat{\hat{\beta}}_3$, $\pi_3(\beta) = \pi_0(\beta)$ and the principal plays a possibly mixed adoption strategy; and for $\beta \in (0, \hat{\beta}_3)$ and $\beta > \hat{\hat{\beta}}_3$, $\pi_3(\beta) < \pi_0(\beta)$ and the principal has an incentive to deviate and not adopt.

Optimal Contracts in Stage 1

We are now in a position to calculate expected profits for the principal in Stage 1, given the principal's priors, the agent's strategy for signaling in Stage 3, and the principal's adoption strategy in Stage 4.

There are two cases to consider, depending on the relative magnitudes of the critical values $\hat{\hat{\beta}}_3$, and $\overline{\beta}$, both defined above.

1. Case 1: $\overline{\beta} > \hat{\hat{\beta}}_3$. Expected profits can be expressed as:

$$\pi^*(\beta) = \begin{cases} \pi_0(\beta) & \text{if } 0 < \beta < \hat{\beta}_3 \\ (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta) & \text{if } \hat{\beta}_3 \leq \beta < \hat{\hat{\beta}}_3 \\ (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_0(\beta) = \pi_0(\beta) & \text{if } \hat{\hat{\beta}}_3 \leq \beta < \overline{\beta} \\ \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \beta \geq \overline{\beta} \end{cases} \tag{A6}$$

2. Case 2: $\overline{\beta} < \hat{\hat{\beta}}_3$. Expected profits can be expressed as:

$$\pi^*(\beta) = \begin{cases} \pi_0(\beta) & \text{if } 0 < \beta < \hat{\beta}_3 \\ (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta) & \text{if } \hat{\beta}_3 \leq \beta < \overline{\beta} \\ \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_3(\beta) & \text{if } \overline{\beta} \leq \beta < \hat{\hat{\beta}}_3 \\ \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \beta \geq \hat{\hat{\beta}}_3 \end{cases} \tag{A7}$$

Note that in both cases the $\pi^*(\beta)$ function is continuous at the critical values. At $\hat{\beta}_3$ and $\hat{\hat{\beta}}_3$, $\pi_3(\beta) = \pi_0(\beta)$ by Lemma 2; at $\overline{\beta}$, $(\rho_1 + \rho_2)\pi_0(\beta) = \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta)$.

Note also that each of the profit functions $\pi_i(\beta)$ for $i \in \{1, 2, 3, 4\}$ is strictly increasing for $\beta < \beta_0$ and strictly decreasing for $\beta > \beta_2$. Hence $\pi^*(\beta)$ is strictly increasing for $\beta < \beta_0$ and strictly decreasing for $\beta > \beta_2$ within each of the intervals defined in (A6) and (A7). Since $\pi^*(\beta)$ is continuous at the critical values, we know $\pi^*(\beta)$ itself is strictly increasing for $\beta < \beta_0$ and strictly decreasing for $\beta > \beta_2$. Hence any maximum for $\pi^*(\beta)$ must lie in the region $\beta \in [\beta_0, \beta_2]$.

Consider Case 1 from above. Since $\hat{\beta}_3 < \beta_0 < \beta_2 < \hat{\hat{\beta}}_3$ by Lemma 2, in the relevant region $\beta \in [\beta_0, \beta_2]$ expected profit is given by: $\pi^*(\beta) = (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta)$. Since both $\pi_0(\beta)$ and $\pi_3(\beta)$ are maximized at β_0, we have that $\pi^*(\beta)$ is maximized at β_0.

Now consider Case 2 from above. If $\overline{\beta} > \beta_2$ then $\pi^*(\beta) = (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta)$ over the relevant range $\beta \in [\beta_0, \beta_2]$ and β_0 is optimal, as in the previous paragraph. If $\overline{\beta} < \beta_2$, then there are two sub-regions to consider: $\beta \in [\beta_0, \overline{\beta})$ and $\beta \in [\overline{\beta}, \beta_2]$. For $\beta \in [\beta_0, \overline{\beta})$, $\pi^*(\beta) = (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta)$ and β_0 is optimal as before. For $\beta \in [\overline{\beta}, \beta_2]$, $\pi^*(\beta) = \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_3(\beta)$. As discussed in Benchmark 2 in Section 6.2.2, this function is maximized by $\widetilde{\beta}$ defined in (3). Hence $\sup_{\beta \in [\overline{\beta}, \beta_2]} \pi^*(\beta) \leq \widetilde{\pi}(\widetilde{\beta})$. By condition (5c), $\widetilde{\pi}(\widetilde{\beta}) < \pi_0(\beta_0)$. By Lemma 2, $\pi_3(\beta) > \pi_0(\beta)$ for $\beta \in [\beta_0, \beta_2]$; this implies $\pi_0(\beta_0) < \pi^*(\beta_0)$ in this region. Hence: $\sup_{\beta \in [\overline{\beta}, \beta_2]} \pi^*(\beta) < \pi^*(\beta_0)$ That is, the choice $\beta = \beta_0$ dominates all $\beta \in [\overline{\beta}, \beta_2]$, in addition to $\beta \in [\beta_0, \overline{\beta})$.

Therefore in both Case 1 and Case 2, β_0 is optimal. The principal has no incentive to deviate. □

A.3 Proof of Proposition 2

We prove by contradiction. Assume that there is a perfect Bayesian equilibrium in which the agent signals truthfully, i.e. signals m_i when the technology is type i, for $i = 1, 2, 3$. We first derive the principal's strategy that must hold in such an equilibrium. We then ask whether the agent has an incentive to deviate, given the strategy of the principal.

In Stage 4, after the agent has revealed truthfully, the principal's optimal adoption strategy is simply: if the signal is m_i, adopt if $\pi_i(\beta) > \pi_0(\beta)$, do not adopt if $\pi_i(\beta) < \pi_0(\beta)$, and play a possibly mixed strategy if $\pi_i(\beta) = \pi_0(\beta)$, where the corresponding ranges of β are given by Lemmas 1-3.

In Stage 1, There are two cases to consider, depending on the relative magnitudes of the critical values $\hat{\beta}_2$ and $\hat{\beta}_3$ defined in Lemmas 1 and 2.

1. Case 1: $\hat{\beta}_3 < \hat{\beta}_2$. Expected profits can be expressed as:

$$\pi^*(\beta) = \begin{cases} \pi_0(\beta) & \text{if } 0 < \beta < \hat{\beta}_3 \\ (\rho_1 + \rho_2)\pi_0(\beta) + \rho_3\pi_3(\beta) & \text{if } \hat{\beta}_3 \le \beta < \hat{\beta}_2 \\ \rho_1\pi_0(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_3(\beta) & \text{if } \hat{\beta}_2 \le \beta < \hat{\hat{\beta}}_3 \\ \rho_1\pi_0(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \hat{\hat{\beta}}_3 \le \beta < \hat{\beta}_1 \\ \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \beta \ge \hat{\hat{\beta}}_1 \end{cases} \tag{A8}$$

2. Case 2: $\hat{\beta}_2 < \hat{\beta}_3$. Expected profits can be expressed as:

$$\pi^*(\beta) = \begin{cases} \pi_0(\beta) & \text{if } 0 < \beta < \hat{\beta}_2 \\ (\rho_1 + \rho_3)\pi_0(\beta) + \rho_2\pi_2(\beta) & \text{if } \hat{\beta}_2 \le \beta < \hat{\beta}_3 \\ \rho_1\pi_0(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_3(\beta) & \text{if } \hat{\beta}_3 \le \beta < \hat{\hat{\beta}}_3 \\ \rho_1\pi_0(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \hat{\hat{\beta}}_3 \le \beta < \hat{\beta}_1 \\ \rho_1\pi_1(\beta) + \rho_2\pi_2(\beta) + \rho_3\pi_0(\beta) & \text{if } \beta \ge \hat{\hat{\beta}}_1 \end{cases} \tag{A9}$$

As in the proof of Proposition 1, in both cases the $\pi^*(\beta)$ function is continuous, since $\pi_3(\beta) = \pi_0(\beta)$ at $\hat{\beta}_3$ and $\hat{\hat{\beta}}_3$ by Lemma 2, $\pi_2(\beta) = \pi_0(\beta)$ at $\hat{\beta}_2$ by Lemma 1, and $\pi_1(\beta) = \pi_0(\beta)$ at $\hat{\beta}_1$ by Lemma 3. Also as in the proof of Proposition 1, $\pi^*(\beta)$ in strictly increasing for $\beta \in (0, \beta_0)$ and strictly decreasing for $\beta > \beta_2$ since each of the $\pi_i(\beta)$ functions is increasing and $\pi^*(\beta)$ is continuous. Hence the principal's optimal β must be in $[\beta_0, \beta_2]$.

Recall that $\hat{\beta}_2 < \beta_0$ (Lemma 1)and $\hat{\beta}_3 < \beta_0 < \beta_2 < \hat{\hat{\beta}}_3$ (Lemma 1). Hence for any β in the range $[\beta_0, \beta_2]$, the principal adopts following signals m_2 or m_3 and does not adopt following signal m_1.

Given this strategy of the principal, the agent has a clear incentive to deviate from truth-telling. If the technology is type 2, the agent is better off signaling m_1 to discourage adoption, since (refer to (A4)), $\frac{(\beta^* s_0)^2}{2} > \frac{(\beta^* s_2)^2}{2}$. Hence there is no perfect Bayesian equilibrium under which the agent reveals truthfully. □

A.4 Proof of Proposition 3

It once more suffices to show that there is no profitable deviation for either principal or agent.

Under this wage schedule, an agent observing a type 2 technology will not want to deviate (and signal something other than m_2) if the following condition holds:

$$\frac{((\beta^{**}+\gamma^{**})s_2)^2}{2} > \frac{(\beta^{**}s_0)^2}{2} \tag{A10}$$

where the left-hand side is the agent's utility if type 2 is adopted, and the right-hand side his utility under the existing technology (refer to A4). Noting that $\beta^{**} = \beta_0$ and $\beta^{**} + \gamma^{**} = \beta_2$ and substituting these values into (2), we have $\pi_2(\beta_2) = s_2^2\beta_2^2 - F$ and $\pi_0(\beta_0) = s_0^2\beta_0^2$. Condition (5a) implies $\pi_2(\beta_2) > \pi_0(\beta_0)$ (since $\pi_2(\beta_0)$ is increasing for $\beta \in [\beta_0, \beta_2)$) and hence (A10). The agent also does not wish to deviate if he observes the other two types for identical reasons as in the proof of Proposition 1.

The principal's next-best strategy is not to pay G and to follow the same strategy as in Proposition 1.[55] The principal will not deviate to this strategy if the following holds:

$$\rho_1\pi_0(\beta_0) + \rho_2\pi_2(\beta_2) + \rho_3\pi_3(\beta_3) - G \quad > \quad (\rho_1+\rho_2)\,\pi_0(\beta^*) + \rho_3\pi_3(\beta^*)$$

where the left-hand side is the payoff to the strategy of Proposition 3 and the right-hand side is the payoff to the strategy of Proposition 1. Condition (7) ensures this holds, since $\beta^* = \beta_3 = \beta_0$. $\square$

A.5 Proof of Proposition 4

To prove the proposition, it again suffices to show that there is no profitable deviation for either principal or agent. First we show there is no incentive for the agent to deviate from his strategy, holding fixed the principal's strategy. Suppose the experimenter offers L in Stage 2. If the technology is of type 1 or 3, the agent has no incentive to deviate, for identical reasons as in Proposition 1. If the technology is of type 2, the agent signals m_2. The agent does not have an incentive to deviate and signal m_1 as this would induce the principal to not adopt which will make him strictly worse off since $U(\beta_0, s_2) = \frac{\beta_0^2 s_2^2}{2} + L > U(\beta_0, s_0) = \frac{\beta_0^2 s_0^2}{2}$ if $L > \frac{\beta_0^2(s_0^2 - s_2^2)}{2}$ as assumed. The agent also has no (strict) incentive to deviate and signal m_3, since this also induces adoption and leads to the same payoff as signaling m_2. Now suppose that the experimenter does not offer L in Stage 2. Then the agent has no incentive deviate for the same reasons as in Proposition 1.

Now we show that there is no incentive for the principal to deviate from her strategy, holding fixed the agent's strategy. First, recall that we assume $G > \rho_2[\pi_2(\beta_2) - \pi_0(\beta_0)]$ and that the principal has a zero probability prior that an experimenter will offer an incentive payment L in

[55] If the principal does not pay G, the agent's strategy is the same as Proposition 1 and we showed that there is no profitable deviation for the principal given the agent's strategy.

Stage 2. Therefore, in Stage 1 the principal is playing the game described in Proposition 1 and so, as shown in the proof for Proposition 1, she has no incentive to deviate if she offers the wage contract $\left(\alpha^* = 0, \beta^* = \frac{p-c_0}{2}\right)$ since it is part of a perfect Bayesian equilibrium for that game.

Now we turn to the principal's decision in Stage 4. There are three possible signals by the agent to consider: If the signal is m_1, then the condition for the principal not to deviate can be written:

$$\pi_0(\beta_0) \geq \pi_1(\beta_0)$$

which is true by Lemma 3. If the signal is m_2, then the condition for the principal not to deviate can be written:

$$\pi_2(\beta_0) \geq \pi_0(\beta_0)$$

where there is no L on the left hand side since we, rather than the principal, pay the lump-sum bonus. This inequality is true by Lemma 1. If the signal is m_3, then the condition for the principal not to deviate can be written:

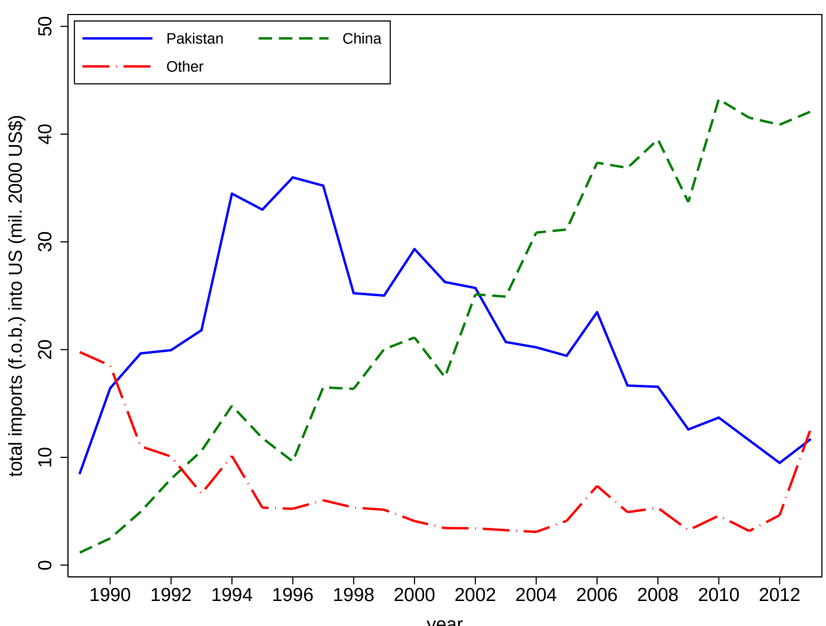
$$\pi_3(\beta_0) \geq \pi_0(\beta_0)$$

which is true by Lemma 2. □

Figure 1: "Buckyball" Design

Notes: Figure shows the standard "buckyball" design. It combines 20 hexagons and 12 pentagons.

Figure 2: U.S. Imports of Inflatable Soccer Balls



Notes: Figure shows import market share within the United States in HS 10-digit category 9506.62.40.80 ("inflatable soccer balls"). Source: United States customs data.

Figure 3: Making the Laminated Sheet (Step 1)

Notes: Figure displays workers laminating a rexine sheet, which is the first stage of producing a soccer ball. Layers of cloth (cotton and/or polyester) are glued to artificial leather called rexine using a latex-based adhesive to form the laminated sheet.

Figure 4: Cutting the Laminated Sheet (Step 2)

Notes: Figure displays a cutter using a hydraulic press to cut hexagons and pentagons from the laminated sheet.

Figure 5: Printing the Designs (Step 3)

Notes: Figure displays a worker printing a logo on the pentagon and hexagon panels.

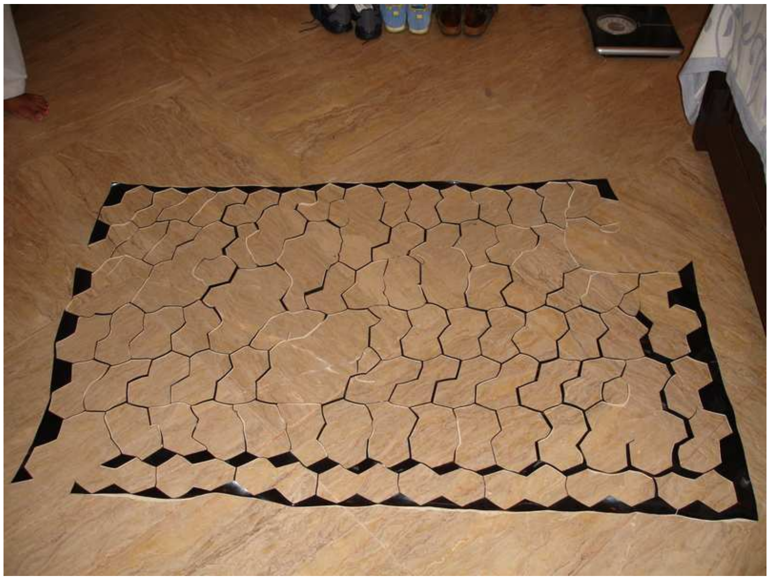
Figure 6: Stitching (Step 4)

Notes: Figure displays a worker stitching a soccer ball. Source: Der Spiegel.

Figure 7: Traditional 2-Hexagon and 2-Pentagon Dies

Notes: Figure displays the traditional two-panel hexagon and pentagon dies.

Figure 8: Laminated Sheet Wastage from Cutting Hexagons



Notes: Figure displays laminated rexine wastage from cutting hexagons with the traditional two-hexagon die.

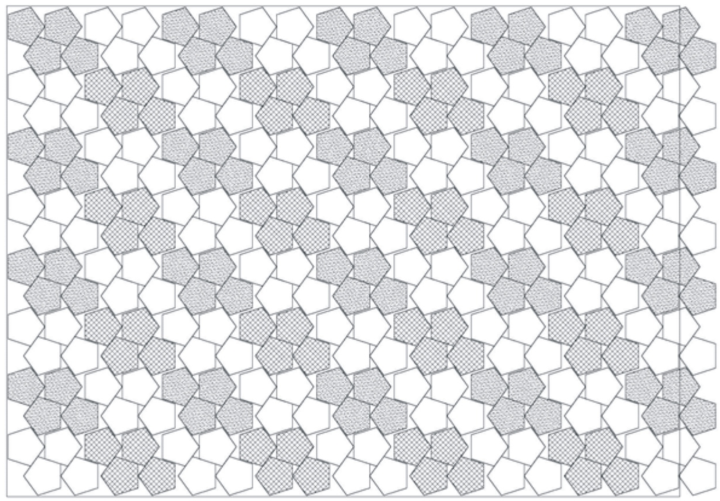
Figure 9: Laminated Sheet Wastage from Cutting Pentagons

Notes: Figure displays laminated rexine wastage from cutting pentagons with the traditional two-pentagon die.

Figure 10: Snapshot from YouTube Video of Adidas Jabulani Production Process

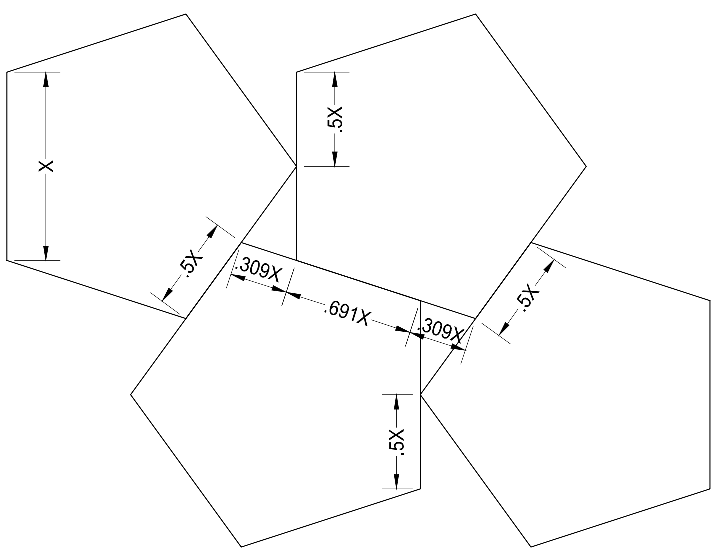
Notes: YouTube video available at http://www.youtube.com/watch?v=zbLjk4OTRdI. Accessed June 10, 2010.

Figure 11: Cutting Pattern for "Offset" Four-Pentagon Die



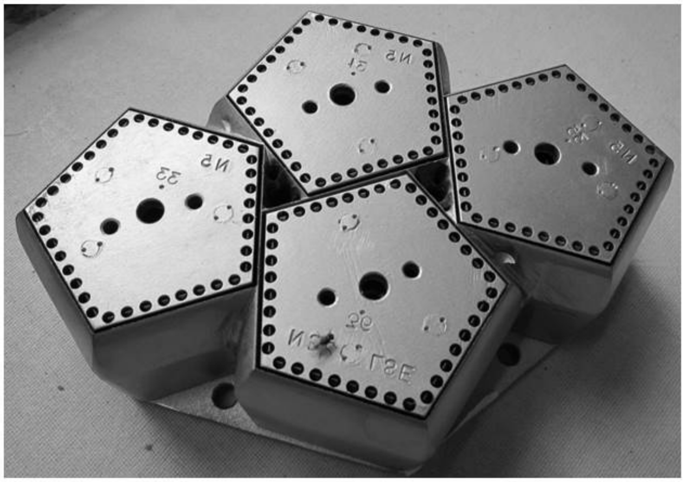
Notes: Figure displays the cutting pattern for the four-panel offset die.

Figure 12: Blueprint for "Offset" Four-Pentagon Die



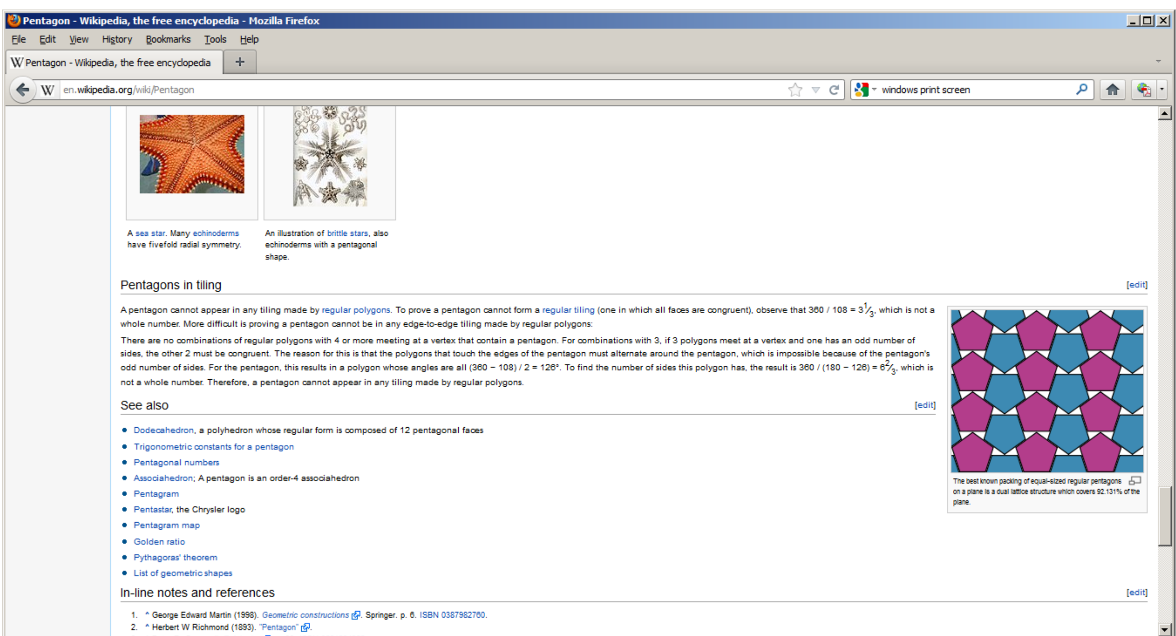
Notes: Figure displays blueprint of the four-panel offset die that was provided to Tech-Drop firms. Blueprint contained instructions for modifying size of die.

Figure 13: The "Offset" Four-Pentagon Die



Notes: Figure displays the four-panel offset die that was provided to Tech-Drop firms.

Figure 14: Wikipedia "Pentagon" Page



Pentagon - Wikipedia, the free encyclopedia - Mozilla Firefox

File Edit View History Bookmarks Tools Help

Pentagon - Wikipedia, the free encyclopedia

en.wikipedia.org/wiki/Pentagon

windows print screen

A sea star. Many echinoderms have fivefold radial symmetry.

An illustration of brittle stars, also echinoderms with a pentagonal shape.

Pentagons in tiling [edit]

A pentagon cannot appear in any tiling made by regular polygons. To prove a pentagon cannot form a regular tiling (one in which all faces are congruent), observe that 360 / 108 = $3\frac{1}{3}$, which is not a whole number. More difficult is proving a pentagon cannot be in any edge-to-edge tiling made by regular polygons:

There are no combinations of regular polygons with 4 or more meeting at a vertex that contain a pentagon. For combinations with 3, if 3 polygons meet at a vertex and one has an odd number of sides, the other 2 must be congruent. The reason for this is that the polygons that touch the edges of the pentagon must alternate around the pentagon, which is impossible because of the pentagon's odd number of sides. For the pentagon, this results in a polygon whose angles are all (360 − 108) / 2 = 126°. To find the number of sides this polygon has, the result is 360 / (180 − 126) = $6\frac{2}{3}$, which is not a whole number. Therefore, a pentagon cannot appear in any tiling made by regular polygons.

The best known packing of equal-sized regular pentagons on a plane is a dual lattice structure which covers 92.131% of the plane.

See also [edit]

- Dodecahedron, a polyhedron whose regular form is composed of 12 pentagonal faces
- Trigonometric constants for a pentagon
- Pentagonal numbers
- Associahedron; A pentagon is an order-4 associahedron
- Pentagram
- Pentastar, the Chrysler logo
- Pentagram map
- Golden ratio
- Pythagoras' theorem
- List of geometric shapes

In-line notes and references [edit]

1. ^ George Edward Martin (1998). Geometric constructions. Springer. p. 6. ISBN 0387982760.
2. ^ Herbert W Richmond (1893). "Pentagon".

Notes: Figure displays the Wikipedia "Pentagon" page. Accessed April 29, 2012.

Figure 15: Adoption of Offset Dies by Firm Z

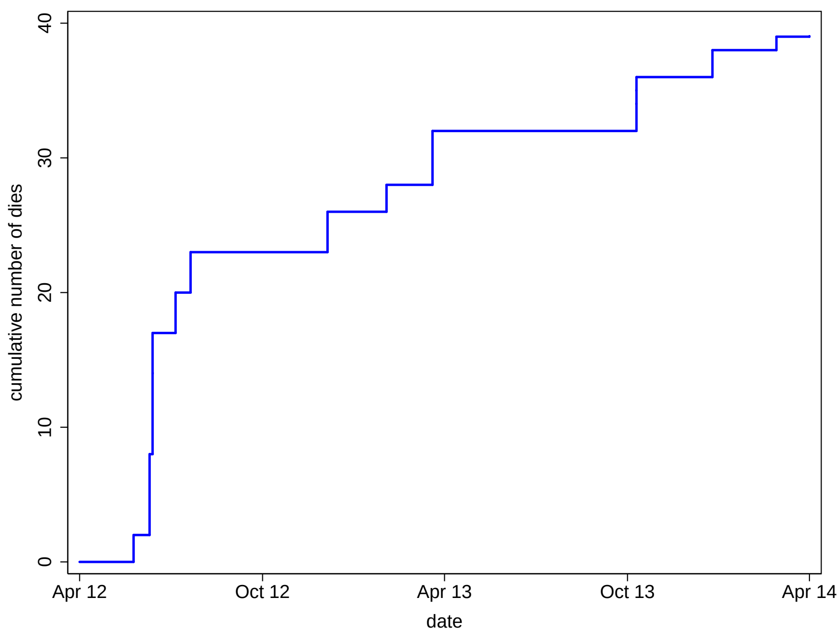
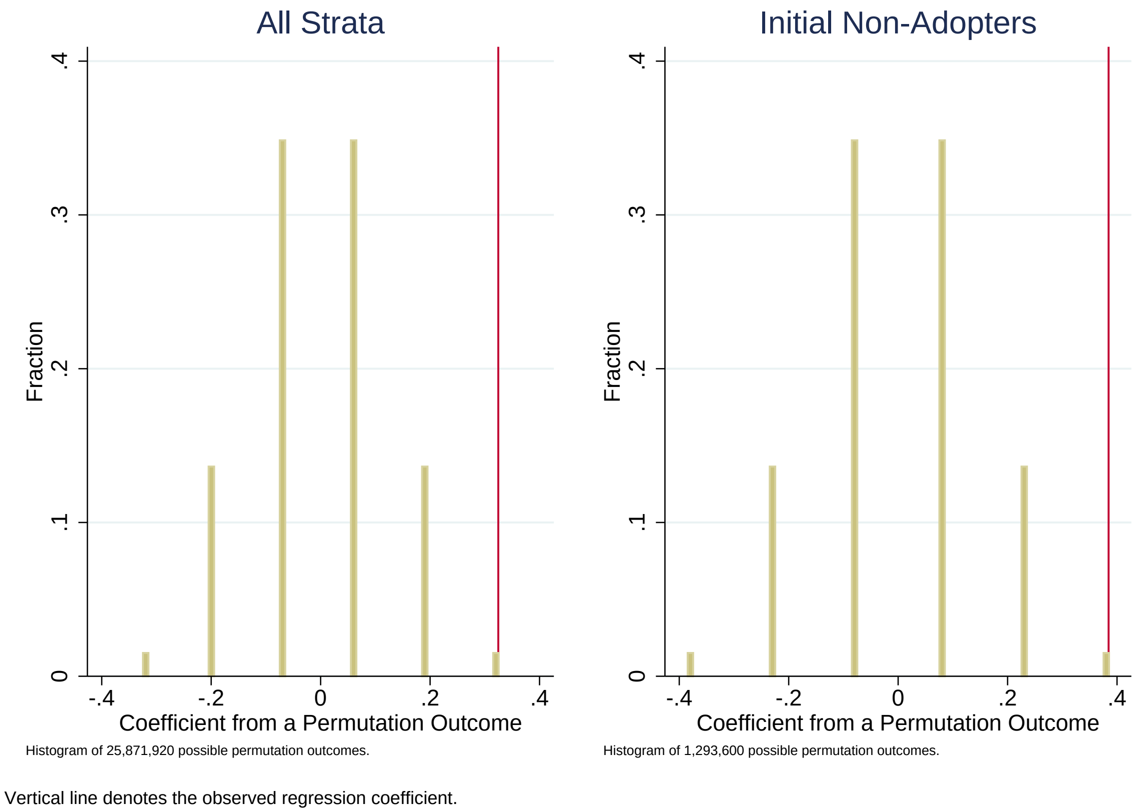
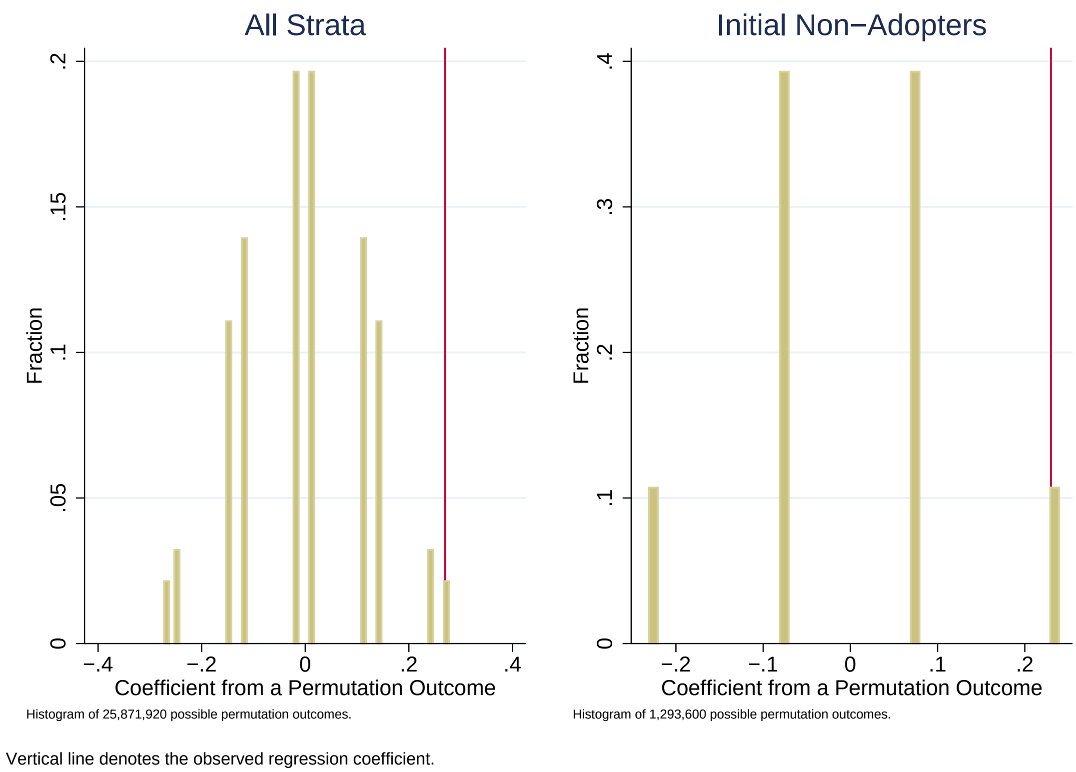


Figure 16: Permutation Outcomes: Current Use



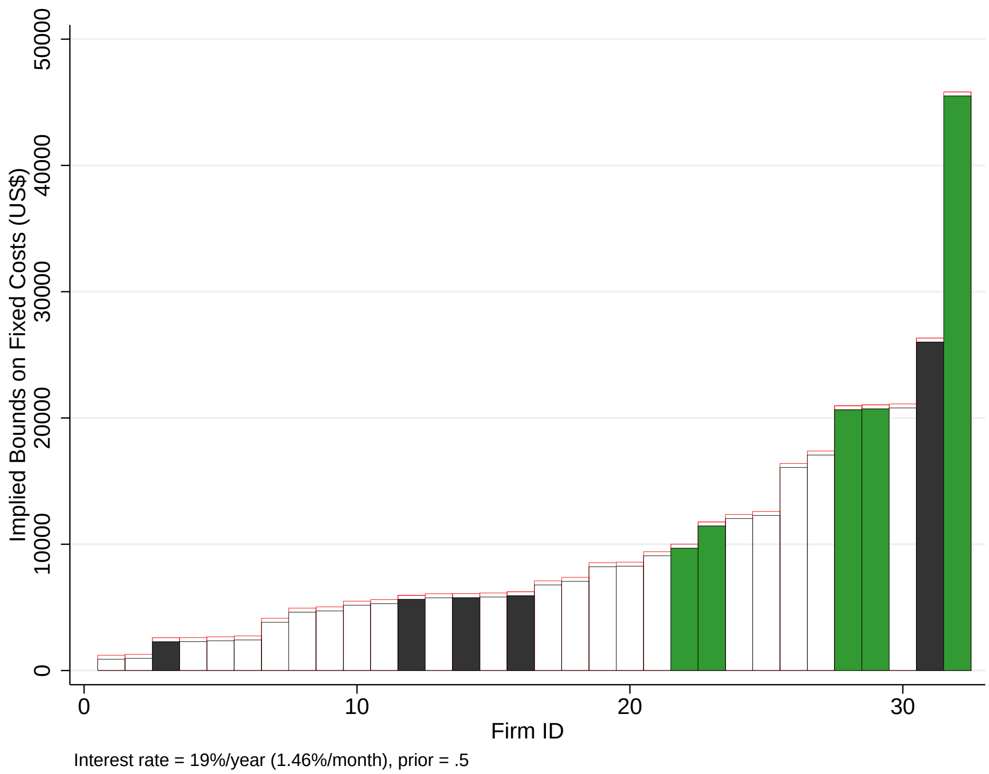
Notes: Figure displays the distribution of outcomes from the permutation tests using current die use as the measure of adoption. The left panel reports outcomes from the specification that includes all firms. The right panel reports outcomes from the specification that includes initial non-adopters only.

Figure 17: Permutation Outcomes: Die Purchase



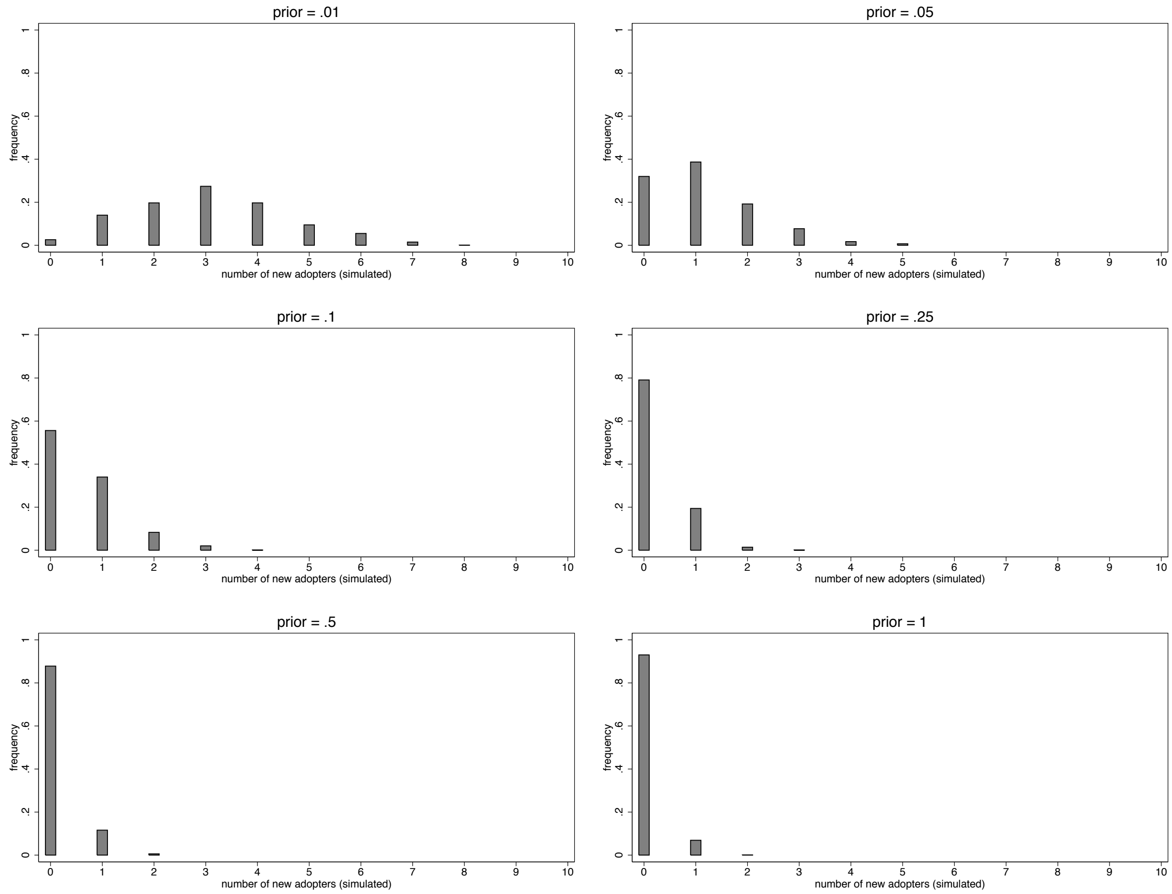
Notes: Figure displays the distribution of outcomes from the permutation tests using die purchases as the measure of adoption. The left panel reports outcomes from the specification that includes all firms. The right panel reports outcomes from the specification that includes initial non-adopters only.

Figure 18: Implied Bounds on Fixed Costs Under a Learning Subsidy Explanation



Notes: Figure displays implied bounds on fixed costs for each firm in incentive-payment intervention, assuming a 19 percent per year interest rate and a prior that the technology works of .5 (see Section 7.3.1). The solid black bars indicate initial adopters and the solid green bars are adopters in response to the incentive treatment. The black outlines indicate the implied lower bounds for non-adopters; the red outlines (which exceed the black outlines uniformly by US$320) indicate the implied upper bounds if firms were to adopt in response to US$320 subsidy.

Figure 19: Effect of Incentive Treatment Under Assumption It Only Reduced Fixed Costs



Notes: Figure displays distribution of number of firms from Group A predicted to respond to incentive intervention by adopting, assuming that the intervention only affects fixed costs (i.e. not priors), based on 1000 simulation draws from a normal distribution with mean and standard deviation in reported in Table 15. See Section 7.3.1.

Table 1: Pentagons per Sheet

	traditional die		offset die	
	owner report (1)	direct obs. (2)	owner report (3)	direct obs. (4)
size 43.5	257.4	257.7	273.5	277.5
	(10.4)	(6.7)	(4.4)	(5.3)
size 43.75	256.3	254.4	269.0	272.0
	(6.2)	(9.4)	(1.4)	(0.0)
size 44	253.8	248.4	280.0	272.5
	(8.4)	(18.7)		(0.7)
size 44.25	246.1	262.0	272.0	
	(8.3)			
rescaled (to size 44)	253.6	248.3	280.0	272.9
	(8.5)	(11.0)	(3.0)	(3.9)
N (after rescaling)	274	39	8	10

Notes: Pentagons per sheet rescaled using means for each size in each column. The N in the final row corresponds to the pooled number of observations for all die sizes. Standard deviations reported in parentheses.

Table 2: Production Costs

Input	Share of Production Costs (%)	Input Cost (in Rs)
rexine	19.79	39.68
	(5.37)	(13.87)
cotton/poly cloth	12.32	23.27
	(4.56)	(8.27)
latex	13.94	38.71
	(10.73)	(90.71)
bladder	21.07	42.02
	(4.87)	(14.09)
labor for cutting	0.76	1.47
	(0.21)	(0.30)
labor for stitching	19.67	39.24
	(5.25)	(12.82)
other labor (laminating, washing, packing, matching)	7.32	15.59
	(4.55)	(13.21)
overhead	5.14	10.84
	(2.05)	(6.10)
total	100.00	210.83
N	38	38

Notes: Column 1 reports the mean cost share per ball of each input using the baseline survey. Column 2 reports the cost of each input in Rupees. Total laminated rexine is the sum of the first three components. The exchange rate is approximately Rs 100 to US$1. Standard deviations reported in parentheses.

Table 3: Benefits from Adopting the Offset Die

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	mean
A. Variable cost reduction						
laminated rexine waste reduction (%)	4.39	5.19	7.93	8.31	13.43	7.69
	(0.46)	(0.41)	(0.30)	(0.05)	(1.18)	(0.22)
laminated rexine as share of cost (%)	34.85	39.87	44.72	51.22	55.44	45.94
	(1.14)	(0.71)	(0.58)	(0.44)	(0.95)	(0.66)
variable cost reduction (%)	0.60	0.80	1.10	1.37	1.94	1.17
	(0.05)	(0.04)	(0.03)	(0.06)	(0.17)	(0.04)
B. Variable cost increase						
cutter wage as share of cost (%)	0.29	0.36	0.45	0.60	0.70	0.48
	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
variable cost increase (%)	0.05	0.06	0.07	0.10	0.12	0.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
C. Net benefits						
net variable cost reduction (%)	0.52	0.72	1.02	1.29	1.87	1.09
	(0.05)	(0.03)	(0.03)	(0.06)	(0.17)	(0.04)
% net variable cost/avg % profit rate	5.27	8.10	12.34	19.86	28.98	15.45
	(0.42)	(0.50)	(0.73)	(1.21)	(2.26)	(0.71)
total cost savings per month (Rs 000s)	4.46	12.19	49.38	165.21	475.01	174.12
	(0.60)	(1.24)	(5.43)	(18.42)	(79.89)	(18.54)
days to recover fixed costs	8.48	15.98	36.61	80.34	193.92	136.94
	(0.97)	(1.68)	(2.93)	(6.51)	(15.64)	(44.54)
days to recover fixed costs (no die)	4.40	8.30	19.01	41.71	100.69	71.10
	(0.51)	(0.87)	(1.52)	(3.38)	(8.12)	(23.13)

Notes: Table reports the distribution of benefits from adopting the offset die. The 1st row reports the rexine waste reduction across firms. The 2nd row reports laminated rexine as a share of unit costs. The 3rd row reports the variable cost reduction from adopting the offset die, computed as the product of a firm's rexine waste reduction, rexine share of cost, and 33 percent (share of pentagons relative to hexagons in total rexine costs). The 4th row reports the cutter's wage as a share of unit costs. The 5th row is the variable labor cost increase percentage from adopting the offset die; this is equal to the product of the cutter share of cost, a 50 percent increase in cutting time using the offset die relative to traditional die, and 33 percent. The 6th row reports the *net* variable cost of reduction, which is the difference between a firm's variable material cost reduction and its variable labor cost increase. The 7th row reports the total cost savings per month in Rupees (the exchange rate is approximately Rs 100 to US$1). The 8th row reports the distribution of the number of days needed to recover all fixed costs of adoption. The 9th row reports the distribution of the number of days needed to recover fixed costs of adoption, excluding purchasing the die; this final row is relevant for treatment firms who received the die for free. As noted in the text, the table uses a hot-deck imputation procedure that replaces a firm's missing value for a particular cost component with a draw from the empirical distribution within the firm's stratum. Since the late responder sample was not asked rexine share of costs (row 2) at baseline, we draw from the empirical distribution of the full sample of initial-responder firms. We repeat this process 1,000 times and report the mean and standard deviations (in parentheses) of each statistic.

Table 4: Firm Characteristics by Quantile

	Mean	Min	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	Max	N
A. Initial-responder sample									
avg output/month (000s)	32.2	0.8	1.6	3.5	10.0	34.6	83.0	275.0	85
avg employment	90.2	3.3	5.2	7.4	20.0	52.9	235.0	1,700.0	85
avg employment (cutters)	5.8	0.5	1.0	1.0	2.2	5.0	13.0	123.0	85
avg Rs/ball (head cutter)	1.5	1.0	1.1	1.3	1.5	1.6	1.9	2.9	79
avg % promotional (of size 5)	41.4	0.0	2.0	18.8	41.1	62.4	80.0	100.0	85
avg price, size 5 promotional	241.3	152.5	185.0	196.3	227.1	266.8	300.0	575.0	64
avg price, size 5 training	440.0	200.0	275.0	313.8	381.3	488.0	600.0	2,250.0	72
avg profit %, size 5 promo	8.2	2.5	3.9	5.2	8.1	10.2	12.5	20.0	64
avg profit %, size 5 training	8.0	1.6	3.2	4.6	8.5	9.9	12.5	22.2	70
avg % lamination in-house	95.7	31.3	81.3	100.0	100.0	100.0	100.0	100.0	75
% standard design (of size 5)	90.7	0.0	70.0	85.0	100.0	100.0	100.0	100.0	80
age of firm	25.4	2.0	6.0	12.0	19.5	36.5	54.0	108.0	84
CEO experience	17.0	3.0	6.0	9.0	15.5	22.0	28.0	66.0	82
head cutter experience	20.5	2.0	8.0	12.0	18.5	26.5	41.0	46.0	36
head cutter tenure	11.1	0.0	2.0	6.0	9.0	15.0	22.0	46.0	35
B. Full sample									
avg output/month (000s)	34.6	0.0	2.0	4.5	15.0	37.2	86.3	278.6	116
avg employment	103.9	3.3	5.6	8.0	25.0	75.0	230.0	2,180.0	115
avg employment (cutters)	5.4	0.5	1.0	1.2	2.8	5.0	12.4	123.0	114
avg Rs/ball (head cutter)	1.5	1.0	1.0	1.3	1.5	1.6	2.0	3.0	107
avg % promotional (of size 5)	37.0	0.0	0.0	8.3	33.8	55.2	80.0	100.0	114
avg price, size 5 promotional	245.7	150.0	185.0	202.0	235.0	270.0	300.0	575.0	81
avg price, size 5 training	465.0	200.0	286.7	330.0	400.0	506.8	667.9	2,250.0	100
avg profit (%), size 5 promo	8.3	2.5	4.1	5.1	7.7	10.4	13.8	20.0	80
avg profit (%), size 5 training	8.3	1.6	3.4	5.1	8.5	10.0	13.0	22.2	95
avg % lamination in-house	96.2	25.0	85.0	100.0	100.0	100.0	100.0	100.0	104

Notes: Variables beginning with "avg. ..." represent within-firm averages across all rounds for which responses are available. Initial responder sample is firms that responded to baseline survey. Piece rate and prices are in Rupees (exchange rate is approximately 100 Rs/US$1). Age, experience and tenure are in years.

Table 5: **Treatment Assignment, Tech-Drop Experiment**

	# Firms			
	Tech Drop	Cash Drop	No Drop	Total
A. Initial responders				
smallest	5	3	12	20
medium-small	6	3	13	22
medium-large	6	3	13	22
largest	6	3	12	21
total	23	12	50	85
B. Late responders				
active, late response	12	5	14	31
active, refused all surveys	0	1	15	16
inactive	7	3	12	22
total	19	9	41	69

Notes: Table reports response rates, by treatment assignment, in the initial-responder sample (Panel A) and the late-responder sample (Panel B). Active firms are those who had produced soccer balls in the previous 12 months and cut their own laminated sheets.

Table 6: Covariate Balance, Tech-Drop Experiment

	Tech Drop	Cash Drop	No Drop
A. Initial responders			
output, normal month (000s)	34.18	26.69	41.56
	(11.48)	(12.15)	(9.53)
output, previous year (000s)	680.17	579.97	763.33
	(220.13)	(225.13)	(232.95)
employment, normal month	42.26	82.58	92.62
	(13.25)	(47.16)	(35.77)
% size 5	84.61	88.96	82.67
	(5.38)	(4.52)	(3.74)
% promotional (of size 5)	50.12	66.09	59.02
	(7.12)	(11.04)	(5.17)
age of firm	22.70	29.25	25.76
	(2.25)	(4.88)	(3.09)
CEO experience	16.22	20.42	16.55
	(2.39)	(2.70)	(1.62)
CEO college indicator	0.43	0.27	0.40
	(0.11)	(0.14)	(0.08)
head cutter experience	17.00	30.33	20.91
	(2.08)	(6.69)	(2.68)
head cutter tenure	12.20	12.00	10.50
	(2.21)	(5.77)	(2.11)
share cutters paid piece rate	1.00	0.83	0.89
	(0.00)	(0.11)	(0.05)
rupees/ball (head cutter)	1.44	1.63	1.37
	(0.14)	(0.21)	(0.10)
N	23	12	50
B. Late responders			
output, normal month (000s)	27.85	34.80	63.13
	(14.01)	(4.99)	(18.25)
employment, normal month	67.20	61.00	353.38
	(48.18)	(34.94)	(264.52)
% size 5	68.00	72.22	96.88
	(9.80)	(16.16)	(3.13)
% promotional (of size 5)	31.17	36.11	24.22
	(9.77)	(12.58)	(13.28)
age of firm	17.40	39.60	35.13
	(3.13)	(16.68)	(5.55)
N	10	5	8

Notes: Table reports balance for initial responders (i.e. responders to baseline) (Panel A) and late responders (Panel B). There are no significant differences in the initial responder sampler. The late responder sample has significant differences, consistent with the observation that response rates responded to treatment assignment among initial non-adopters. Standard errors in parentheses.

Table 7: Adoption of Technology as of August 2013

	Tech Drop	Cash Drop	No Drop	Total
A. Initial-responder sample				
# ever active firms	23	12	50	85
# ever responded	23	12	50	85
# currently active and ever responded	22	11	46	79
# traded in	15	0	0	15
# ordered new die (beyond trade-in)	1	0	4	5
# received new die (beyond trade-in)	1	0	2	3
# ever used new die (>1000 balls)	4	0	0	4
# currently using new die (>1000 balls)	4	0	0	4
B. Full sample				
# ever active firms	35	18	79	132
# ever responded	35	17	64	116
# currently active and ever responded	32	15	59	106
# traded in	19	0	0	19
# ordered new die (beyond trade-in)	1	0	6	7
# received new die (beyond trade-in)	1	0	4	5
# ever used new die (>1000 balls)	5	0	1	6
# currently using new die (>1000 balls)	5	0	1	6

Notes: Table reports adoption statistics as of August 2013 in the initial-responder sample (Panel A) and the full sample (Panel B). The first three rows in each panel are the number active and responder firms. "# ever responded" is the number of firms that answered at least one of the surveys across rounds. The 4th row reports the number of firms that availed themselves of the option to trade in the 4-panel offset die for a different offset die. The discrepancy between 5th and 6th rows is that one diemaker was particularly slow in delivering an offset die and the firm subsequently canceled the order. The 7th row indicates the number of firms that ever report using the die, and the 8th row is the number of firms that were using the die (to produce at least 1,000 balls) as of August 2013.

Table 8: Correlates of Adoption: Scale & Quality Variables (Initial-Responder Sample)

	Dep. var.: indicator for currently using offset die									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
tech drop group	0.18**	0.18**		0.59						0.17**
	(0.08)	(0.08)		(0.51)						(0.07)
cash drop group		-0.00								
		(0.02)								
log avg output/month			0.03	0.04*		0.03				0.06
			(0.03)	(0.02)		(0.03)				(0.04)
log avg output*tech drop				-0.04						
				(0.05)						
share standard (of size 5)					-0.39	-0.38				-0.44
					(0.32)	(0.33)				(0.27)
log avg price, size 5 training							-0.06			-0.19*
							(0.05)			(0.11)
avg share promotional (of size 5)								-0.11		-0.16
								(0.07)		(0.10)
avg profit rate, size 5 training									0.54	0.37
									(0.64)	(0.62)
constant	0.02	0.02	-0.22	-0.29	0.41	0.14	0.40	0.11	0.02	1.14*
	(0.05)	(0.05)	(0.22)	(0.18)	(0.32)	(0.45)	(0.31)	(0.07)	(0.05)	(0.67)
stratum dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.22	0.22	0.10	0.25	0.16	0.18	0.09	0.10	0.10	0.37
N	79	79	79	79	74	74	68	79	66	63

Notes: Table reports linear probability regressions of technology adoption, measured as current use, on firm characteristics for the initial-responder sample. Variables beginning with "avg. ..." represent within-firm averages across all rounds for which responses are available. All regressions include stratum dummies. Significance: * .10; ** .05; *** 0.01.

Table 9: Correlates of Adoption: Manager & Cutter Characteristics (Initial-Responder Sample)

	Dep. var.: indicator for currently using offset die										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
tech drop group	0.18**										0.22**
	(0.08)										(0.09)
CEO university indicator		0.04									0.01
		(0.07)									(0.07)
CEO experience (/100)			-0.24								-0.21
			(0.17)								(0.28)
age of firm (/100)				-0.06							0.03
				(0.09)							(0.16)
cutters paid piece rate					0.02						-0.04
					(0.03)						(0.05)
Rs/ball, head cutter						0.11					
						(0.15)					
head cutter experience (/100)							-0.03				
							(0.09)				
head cutter tenure (/100)								-0.19			
								(0.23)			
cutter raven's score									-0.01		
									(0.03)		
avg pent/sheet, rescaled (/100)										0.65*	-0.04
										(0.37)	(0.45)
log avg output/month											0.05
											(0.04)
constant	0.02	0.05	0.11	0.07	0.04	-0.10	0.00	0.03	0.03	-1.58*	-0.24
	(0.05)	(0.05)	(0.07)	(0.05)	(0.04)	(0.19)	(0.01)	(0.03)	(0.07)	(0.90)	(0.99)
stratum dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.22	0.09	0.09	0.08	0.09	0.11	0.12	0.12	0.18	0.12	0.31
N	79	70	77	78	75	74	33	32	37	70	56

Notes: Table reports linear probability regressions of technology adoption, measured as current use, on manager and cutter characteristics for the initial-responder sample. "Cutters paid piece rate" is an indicator of if the cutter is paid a piece rate. "Rs/ball, head cutter" is the rupee payment per ball to the head cutter. Variables beginning with "avg. ..." represent within-firm averages across all rounds for which responses are available. All regressions include stratum dummies. Significance: * .10; ** .05; *** 0.01.

Table 10: Reasons for Non-Adoption (Technology Group Sample)

firm	no orders to try on	too busy	doubt profitable	waiting for others to prove value	waiting for others to iron out kinks	cutters unwilling	printing problems	other production issues	other
1	2	3					1		
2	2						1		
3	2						1		
4	2						1		
5	2					1			
6	4		3			1	2		
7	3		2			1			
8	3					1	2		
9	3	2				1			
10	1								
11	1								
12	1								
13	3					1	2		
14	3					1	2		
15	2					1			3
16	1								
17	5	3				1	2	4	
18	2	3				1			3

Notes: Table reports responses of 18 tech-drop firms from the March-April 2013 survey round.

Table 11: Covariate Balance, Incentive-Payment Experiment

	Group A Incentive Contract	Group B No Incentive Contract
log avg output/month	9.86	9.31
	(0.41)	(0.29)
log avg employment	3.35	3.23
	(0.38)	(0.25)
log avg price, size 5 promo	5.40	5.45
	(0.02)	(0.07)
log avg price, size 5 training	6.00	5.93
	(0.06)	(0.06)
avg % promotional (of size 5)	34.90	32.04
	(6.20)	(7.26)
avg Rs/ball, head cutter	1.45	1.63
	(0.10)	(0.15)
CEO university indicator	0.56	0.36
	(0.18)	(0.15)
CEO experience	15.50	16.50
	(3.60)	(3.60)
age of firm	24.53	20.60
	(2.83)	(2.28)
N	15	16

Notes: Table reports baseline balance in the Incentive-Payment Experiment. This sample is the 31 tech-drop firms from the Tech-Drop Experiment who were active as of September 2013. There are no statistical difference between treatment and control groups. Standard errors reported in parentheses.

Table 12: "Test" Results

firm	1	2	3	4	5	6	7	8	9	10
time	2:52	2:40	3:03	3:02	2:59	2:28	2:25	2:45	2:30	2:50
die size	43.5	43.75	44	44	43.5	43.5	43.5	43.5	44	43.5
# pentagons	270	272	273	272	282	279	279	272	272	267

Notes: Table reports the times achieved by cutters at the 10 Group A firms who agreed to the incentive payment intervention. The 2nd row reports the time, in minutes, to cut a single rexine sheet with the offset die. The 3rd row reports the size of the die (in mm) used by the cutter. The 4th row reports the number of pentagons achieved. Note that the average time to cut with the traditional die is 2:15.

Table 13: Incentive-Payment Experiment Results (Current Use as Outcome)

	Dep. var.: currently using offset die and produced $> 1,000$ balls							
	All Strata				Initial Non-Adopters			
	First Stage (1)	OLS (2)	Reduced Form (ITT) (3)	IV (TOT) (4)	First Stage (5)	OLS (6)	Reduced Form (ITT) (7)	IV (TOT) (8)
rec'd treatment		0.48***		0.48***		0.59***		0.63***
		(0.15)		(0.15)		(0.18)		(0.18)
assigned to group A	0.68***		0.32**		0.62***		0.38***	
	(0.12)		(0.12)		(0.14)		(0.13)	
stratum dummies	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.57	0.69	0.60	0.69	0.50	0.57	0.36	0.57
N	31	31	31	31	26	26	26	26

Notes: Table reports results of incentive-payment experiment on adoption rates using current use as the measure of adoption. The left panel includes all firms. For this sample, the p-value testing the null hypothesis that treatment has no effect in the ITT specification using 25,872,000 possible permutations of treatment assignment is 3.04 percent. The right panel includes only initial non-adopter firms. For this sample, the corresponding p-value from the possible 1,293,600 permutations is 3.04 percent. All regressions include stratum dummies. Significance: * .10; ** .05; *** 0.01.

Table 14: Incentive-Payment Experiment Results (Die Purchase as Outcome)

	Dep. var.: purchased first offset die (beyond trade-in) after Sept. 1, 2013							
	All Strata				Initial Non-Adopters			
	First Stage	OLS	Reduced Form (ITT)	IV (TOT)	First Stage	OLS	Reduced Form (ITT)	IV (TOT)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rec'd treatment		0.42**		0.40**		0.40**		0.38**
		(0.15)		(0.16)		(0.16)		(0.17)
assigned to group A	0.68***		0.27**		0.62***		0.23*	
	(0.12)		(0.12)		(0.14)		(0.12)	
stratum dummies	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.57	0.40	0.24	0.40	0.50	0.40	0.22	0.40
N	31	31	31	31	26	26	26	26

Notes: Table reports results of incentive-payment experiment on adoption rates using additional die purchases (beyond the trade-in offer) after September 2013 as the measure of adoption. he left panel includes all firms. For this sample, the p-value testing the null hypothesis that treatment has no effect in the ITT specification using 25,872,000 possible permutations of treatment assignment is 4.28 percent. The right panel includes only initial non-adopter firms. For this sample, the corresponding p-value from the possible 1,293,600 permutations is 21.42 percent. All regressions include stratum dummies. Significance: * .10; ** .05; *** 0.01.

Table 15: Quantitative Plausibility of Learning-Subsidy Explanation

	Value of prior					
	.01	.05	.1	.25	.5	1
	(1)	(2)	(3)	(4)	(5)	(6)
A. Estimates of fixed costs						
estimate of θ	6.58***	7.67***	8.29***	9.17***	9.85***	10.53***
	(0.41)	(0.28)	(0.27)	(0.27)	(0.27)	(0.27)
estimate of σ_ε	1.65**	1.23***	1.20***	1.19***	1.18***	1.18***
	(0.64)	(0.43)	(0.39)	(0.38)	(0.37)	(0.37)
B. P-values of observing ≥ 5 adopters in incentive experiment						
	0.166	0.007	0.000	0.000	0.000	0.000
C. ITT estimate						
assigned to group A	0.22**	0.08	0.04	0.02	0.01	0.01
	(0.11)	(0.08)	(0.06)	(0.03)	(0.03)	(0.02)
N	31	31	31	31	31	31

Notes: Sample is tech-drop firms still active at time of second experiment (Sept. 2013). Estimates for for θ and σ_ε come from maximizing the likelihood function in (11)-(**??**). P-values based on 1000 simulation draws of log fixed costs from normal distribution with mean $\hat{\theta}$ and standard deviation $\hat{\sigma}_\varepsilon$ for corresponding value of prior. Panel C reports average and standard deviation of the ITT estimates across the 1000 simulations. Significance: * .10; ** .05; *** 0.01.

Table A.1: Means by Firm Size Bin

	Firm Size Bins 1	2	3	4	Late Responders
A. Initial-responder sample					
avg output/month (000s)	5.43	6.18	24.49	93.08	
avg employment	11.68	13.29	53.07	284.43	
avg employment (cutters)	1.25	1.79	3.84	16.36	
cutters paid piece rate indicator	0.90	1.00	0.91	0.84	
avg Rs/ball (head cutter)	1.53	1.54	1.51	1.38	
avg % promotional (of size 5)	49.44	51.40	34.47	30.61	
avg price, size 5 promotional	239.57	223.76	249.23	254.26	
avg price, size 5 training	387.09	329.23	442.18	617.36	
avg profit %, size 5 promo	6.15	7.20	9.58	10.16	
avg profit %, size 5 training	6.95	7.00	8.25	9.86	
avg % lamination in-house	90.64	92.74	99.77	99.82	
% standard design (of size 5)	89.00	94.43	90.00	89.21	
age of firm	16.95	20.09	24.67	39.81	
CEO experience	19.00	16.55	15.75	16.85	
head cutter experience	13.83	20.44	26.82	17.60	
head cutter tenure	12.50	7.33	13.55	11.00	
N	20	22	22	21	
A. Full sample					
avg output/month (000s)	5.43	6.18	24.49	93.08	41.23
avg employment	11.68	13.29	53.07	284.43	142.65
avg employment (cutters)	1.25	1.79	3.84	16.36	4.42
avg Rs/ball (head cutter)	1.53	1.54	1.51	1.38	1.61
avg % promotional (of size 5)	49.44	51.40	34.47	30.61	23.93
avg price, size 5 promotional	239.57	223.76	249.23	254.26	262.34
avg price, size 5 training	387.09	329.23	442.18	617.36	529.49
avg profit %, size 5 promo	6.15	7.20	9.58	10.16	8.68
avg profit %, size 5 training	6.95	7.00	8.25	9.86	9.29
avg % lamination in-house	90.64	92.74	99.77	99.82	97.41
N	20	22	22	21	31

Notes: Size bins are defined as quartiles of output in a normal month from baseline survey. Same bins are used as strata in technology-drop experiment. Late responders (i.e. who did not respond at baseline) could not be assigned to a size bin by this definition. Piece rate and prices are in Rupees (exchange rate is approximately 100 Rs/US$1). Age, experience and tenure are in years.